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ESSAYS ON ENERGY ECONOMICS

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LEONARDO CHAVES BORGES CARDOSO

ESSAYS ON ENERGY ECONOMICS

Thesis submitted in a partial fulfilment of the requirements for degree of doctorate in Economic Development, Program of Economic Development, Sector of Applied Social Sciences, at Federal University of Paraná.

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ABSTRACT

This thesis consists of three distinct essays (chapters) on Energy Economics. First Essay estimates marginal effects of ethanol and gasoline demands. In addition to the core marginal effects (price and income), cross prices marginal effects have special appealing in the Brazilian fuel market because of flex fuel cars policy (after 2003). Regarding estimation strategies, we performed non-neighbors purchase prices as instruments for ethanol and gasoline prices to solve endogeneity issues. Results showed ethanol´s price elasticities around -1.5 and gasoline´s elasticities around -0.8. After flex fuel cars introduction, both demands had larger cross price elasticities, indicating that biofuels likely decreased dependence of consumers for each fuel separately. The Second Essay is related to volatility price transmission between oil and agricultural commodities. It aims to test if there are differences into volatility transmission from oil to two agricultural commodities groups: i) energy agricultural commodities (EAC), used in biofuels production; ii) non-energy agricultural commodities (NAC), not used in biofuels productions. In order to do that, I used Mgarch models on monthly basis and found that price volatility spillovers became stronger for both groups (EAC and NAC), but with opposite directions. EAC returns and Oil returns moved in the same direction over time, and in 2008 this conditional correlation became more positive. On the other hand, Oil and NAC returns moved in opposite direction, and during Financial Crisis they became more negative. The Third Essay investigated the price transmission strategies in gas station market. In a competitive market situation a symmetric price transmission is expected, where the speed of adjustment of the market should be equal, no matter which direction input prices are going (up or down). Any deviation from this situation is called as price asymmetry transmission. Price transmission has direct implications for welfare distribution, positive price asymmetry (when firms react faster to increases in input prices than decrease in inputs). Stressed the importance of studying price asymmetry, this third essay aims to answer three questions: i) Is there price asymmetry in Brazilian Gasoline Market? ii) Is asymmetry a firm or a market feature? iii) Which variables contribute to the likelihood of gas stations to respond asymmetrically? To answer these we run an AECM for more than 17,000 gas stations. Results indicate that there is heterogeneity across gas stations: 71% of them have no asymmetry, 23% have positive asymmetry and 6% have negative asymmetry. Regarding the importance of variables on the probability to respond asymmetrically: gas stations with higher margins, less rivals nearby and non-white flags have higher probability to have positive asymmetry, reinforcing linkage between positive asymmetry and market power. These results reinforce the link between power market and positive price asymmetry and bring the novelty of relating positive asymmetry to spatial competition.

Keywords: Panel, Fuels, Gas Stations, Volatility Transmission, Asymmetry.

RESUMO

Essa tese é composta por três ensaios distintos. O primeiro ensaio tem por objetivo calcular as elasticidades marginais das demandas por etanol e gasolina. Além dos efeitos marginais sobre o preço e sobre a renda, a introdução dos carros flex gerou a necessidade de calcular também as elasticidades cruzadas. Sobre as estratégias de estimação, usamos preços de compra dos não-vizinhos como instrumento para os preços da gasolina e do etanol, controlando problemas de endogeneidade. Os resultados indicam que o etanol tem elasticidade preço de -1,5 e a gasolina elasticidade de -0,8. A influência dos carros flex fuel também é notada com o aumento das elasticidades cruzada pós 2003 (ano da introdução dos carros flex). O segundo ensaio investiga a transmissão de volatilidade entre o petróleo e as commodities agrícolas. A pergunta é se existem diferenças na transmissão de volatilidade entre petróleo e dois grupos de commodities agrícolas, Energy Agricultural Commodities (EAC) e Non-Energy Agricultural Commodities (NAC). O que diferencia os dois grupos é uso de suas commodities para fabricação de biocombustíveis, o grupo EAC é usado na fabricação de biocombustíveis, o NAC não. Os resultados indicam que existe transmissão de volatilidade e que essa transmissão aumentou durante o período da Crise Financeira de 2008. Essas mudanças na integração dos mercados indicam para revisão das estratégias de diversificação dos investidores e das políticas públicas. O terceiro ensaio investiga assimetria de preços nos postos brasileiros. Em um mercado competitivo, transmissão simétrica de preços é esperada. A velocidade do ajuste aos choques não deve ser diferente para choques positivos ou negativos. Qualquer desvio desse padrão é chamado de assimetria de preços. Transmissão de preços impacta na redistribuição dos excedentes. Quando as firmas reagem mais rápido a aumento dos custos do que à diminuição desses (assimetria positiva) existe uma transferência de excedente dos consumidores para os produtores. Se ocorre o contrário, a velocidade é maior quando os preços dos insumos caem do que quando eles sobem (assimetria negativa), os consumidores estarão em uma melhor situação. Dito isso, o terceiro ensaio tenta responder a três perguntas: i) Existe assimetria de preço no mercado brasileiro? ii) Assimetria é uma característica das firmas ou do mercado como um todo? iii) O que aumenta ou diminui a chande de um posto praticar assimetria? Foi usado um AECM para mais de 17 mil postos e os resultados indicam para a existência de heterogeneidade: 71% responde simetricamente, 23% possui assimetria positiva e 6% possui assimetria negativa. A respeito de quais variáveis mudam as chances de uma firma responder assimetricamente, os postos com maiores margens e com bandeira diferente da branca possuem maior probabilidade de ter assimetria positiva, reforçando o link entre assimetria positiva e poder de mercado. Os postos com menos vizinhos num raio de 0.5 possuem maior chance de praticar assimetria positiva, o que, até onde sabemos, é o primeiro resultado relacionando concorrência espacial e assimetria positiva.

Palavras-chave: Painel, Combustíveis, Postos, Volatilidade, Assimetria.

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INTRODUCTION

This thesis consists of three distinct essays on Energy Economics. Each essay has its own database and econometric approach; the first used a panel data for Brazilian States; the second one used commodities prices in a Mgarch model; and the last used AECM in a georeferenced dataset for gas stations in Brazil.

The first essay, "Biofuels Policies and Fuel Demand Elasticities in Brazil: an IV approach", estimates fuel elasticities in Brazil. The pioneering of Brazil on biofuel policies increases the motivation of to calculate these elasticities, it became Brazil in a mirror of what could happen in case of other countries to adopt similar policies. In this sense, the first main question is to calculate marginal effects of ethanol and gasoline demands. Due to the possibility of substitution of these fuels in each demand caused by flex fuel cars introduction after 2003, cross prices marginal effects gained importance, needing to be added into empirical estimations. In the econometric strategy I used non-neighbors purchase prices as price instruments to try to solve endogeneity issues. Price endogeneity has a well-known downward bias, so, controlling it, an upward revision on marginal effects is expected. In fact, my estimates, and more recent literature revised elasticities, in direction to increase them. My results indicated to ethanol elasticity prices around -1.5 and gasoline's elasticities around -0.8.

Still regarding first essay, the influence of flex fuel cars on demands were in direction to include flexibility on those. Both of them (ethanol and gasoline demands) became more elastic regarding own prices and regarding cross prices. It seems that dependence of consumers to each individual fuel decreased after the introduction of flex fuel cars, as expected. To see the differences of marginal effects along the time, it was used two dummies to separate periods in three parts and it was also estimated around 90 regressions moving forward just one month in each new estimation. These procedures allowed to verify the irrelevance of cross price elasticities in the beginning of sample (2001) and their gained importance (they became relevant statistically) after flex fuel introduction.

The second essay, "Price Volatility Transmission from Oil to Energy and Non-Energy Agricultural Commodities", aims to investigate the volatility transmission between oil and agricultural commodities. There is a first transmission linkage between oil and agricultural commodities: fertilizers are an important input and they are oil-intensive. Recently, biofuels likely increased the linkage between oil and agricultural commodities by demand side. This higher integration likely increased price and volatility transmission from oil to agricultural commodities. The question in this second chapter is if there are differences in volatility transmission from oil to agricultural commodities with this extra linkage by biofuels and the group of agricultural commodities that has only the traditional linkage by fertilizers. The econometric strategy to answer that was to run a MGARCH model from oil indexes to two agricultural commodities indexes, the first called by Energy Agricultural Commodities (EAC), which is composed by agricultural commodities widely used in biofuels production, and the second called by Non-Energy Agricultural Commodities (NAC), which is composed by mainly agricultural commodities that are not widely used in biofuels production.

Results of essay two indicate that actually there is a higher volatility transmission from oil to Energy Agricultural Commodities and this integration became even stronger during Financial Crisis of 2008. Hence, during the moment when diversification became more important, integration became higher. Summing up, public policies and diversification strategies used by traders should be revised in direction to distinguish agricultural commodities regarding this extra linkage with biofuels. Here, it is possible to establish some link between first and second essay, since the introduction of flex fuel cars by itself increases linkage between oil and agricultural commodities, but mandates (government obligates to mix some percent of biofuel into fossil fuel) increase integration even more and are not indicated if price volatility is a concern.

In the third essay, "Price Asymmetry and Retailers Heterogeneity in Brazilian Gas Stations", I returned to a Brazilian Database and the central question is regarding pricing strategies. In a competitive market situation a symmetric price transmission is expected, the speed of adjustment of the market should be equal, no matter in which direction input prices are going (up or down). When input prices increase, firms need to pass on costs to avoid negative profit situation. When they go down, firms' reaction is in a direction to avoid market share losses. Therefore, if firms react faster when input prices increase than when they decrease (positive asymmetry), it means a capture of consumers' surplus by the firms. When firms's reacion is slowly when input prices decrease than when they decrease (negative asymmetry), the surplus transference is from firms to consumers.

So far, studies regarding price asymmetry in Brazil used only aggregated database, which likely suffers by summation bias. In a hypothetical city with just two gas stations, one with positive asymmetric behaviour and other with negative one, there is a high chance that this city accepts the null of a symmetric behaviour. The present study will try to overcome this problem with a gas station level dataset. The National Agency for Petroleum, Natural Gas and Biofuels (ANP) has a detailed database with weekly information for gas stations in an unbalanced panel data, where more than 40% of population is covered every week. This firm-level database has information such as purchase and selling price for gasoline, name of gas stations, brand and complete address. This information allows to answer if there is price asymmetry in Brazil at firm-level. Because database has more than 2 millions of observations for more than 17.000 different gas stations, it is possible to also obtain results of price asymmetry against fixed effects to check which of these effects matter to change the likelihood of firms to have price asymmetry. Results indicate that there is heterogeneity regarding price transmission among firms: 71% of gas stations had no asymmetry, 23% had a positive asymmetry pattern and 6% of them had negative asymmetry. Regarding which fixed effects could explain the probability to have a positive asymmetry, higher margins, a minor number of rivals nearby and be a non-white flag increase the probability of having positive asymmetry. These results strength relations between market power and positive asymmetry and inaugurate a link between spatial competition and price asymmetry transmission.

This thesis has, besides this introduction, three independent chapters. Chapter One entitled by "Biofuels Policies and Fuel Demand Elasticities in Brazil: an IV approach" (p. 16), followed by the Chapter Two entitled by "Price Volatility Transmission from Oil to Energy and Non-Energy Agricultural Commodities" (p. 45) and the last essay entitled by "Price Asymmetry and Retailers Heterogeneity in Brazilian Gas Stations" (p. 79). After the three chapters, I finally conclude with a chapter dedicated to the Final Remarks (p. 104) where the advances of this work will be highlighted and future researches will be suggested.

1 BIOFUELS POLICIES AND FUEL DEMAND ELASTICITIES IN BRAZIL: AN IV APPROACH

Abstract

Estimating marginal effects of fuel demands is a central issue in order to prescribe appropriate public policies. In addition to the core marginal effects (price and income) of a regular fuel demand estimation, cross prices marginal effects have special appealing in the Brazilian fuel market because of increasing of possibilities of arbitrage between gasoline and ethanol after flex fuel cars introduction. Regarding estimation strategies, we performed non-neighbors purchase prices as instruments for ethanol and gasoline prices trying to solve endogeneity issues. Results showed ethanol´s price elasticities around -1.5 and gasoline´s elasticities around -0.8. Flex fuel cars introduction seems to cause higher elasticities for both demands, increasing their price responses of both demands.

Keywords: Ethanol, Gasoline, Panel Data, Instrumental Variables, Endogeneity.
JEL:Q41, Q4, C26.

Resumo

Brasil é um pioneiro em políticas ambientais. Antigas preocupações (diversificação da matriz energética e desenvolvimento rural) e novas preocupações (preocupações ambientais) trabalham em conjunto envidenciando a necessidade de um melhor conhecimento dos mercados de etanol e gasolina. No intuito de contribuir com essa tarefa, calcular os efeitos marginais dessas demandas é central para prescrever políticas públicas. Em adição aos principais efeitos marginais das demandas por combustíveis (elasticidade preço e elasticidade renda), a demanda brasileira traz um apelo a mais com a necessidade de serem calculados também os efeitos marginais cruzados. Essa necessidade veio com a introdução dos carros flex fuel no mercado após 2003. Sobre as estratégias de estimação, usamos preços de compra dos não-vizinhos como instrumento para os preços da gasolina e do etanol, controlando problemas de endogeneidade. Os resultados indicam que o etanol tem elasticidade preço de -1,5 e a gasolina elasticidade de -0,8. A influência dos carros flex (pós-2003) é percebida com aumentos das elasticidades preço e preço cruzada para ambos os combustíveis, o que permite concluir que os carros flex diminuiram a dependência dos consumidores em relação a cada combustível, aumentando as respostas da demanda a preços.

Palavras-chave: Etanol, Gasolina, Demanda, Painel de Dados, Variáveis Instrumentais, Endogeneidade.

1.1 INTRODUCTION

Biofuels is a convergent point of some major challenges for the world. They have implications for climate change, energy security and food competition. In Brazil biofuels policies began in 1970s for two main reasons: i) to reduce oil dependence; ii) to increase rural development. At that time, there was a perfect scenario to welcome biofuels policies. Oil crisis multiplied by 5 oil prices between Oct/1973 and March/1974 which deteriorated the trade balance of oil importers. In addition to this, lower sugar prices were putting down revenue of sugar cane farmers in Brazil. Hence, decision to produce ethanol from sugar cane reached many goals, reducing oil dependence and, improving trade balance and subsidizing local farmers.

During 1980s oil prices fall and, with oil prices, and so does the interest on biofuels in Brazil. This high correlation between oil prices and interest on biofuels is also verified in their countries[1].

During 2000s a new age of high oil prices rose the interest on biofuels policies again. At this time, environmental concerns and oil prices´ volatility were added to the list of biofuels motivations. Mainly after 2008, due to the food crisis with the increasing of the most agricultural commodities prices and increasing of price volatility, the discussion about competition between biofuels and food returned, making the two major economies (Europe and US) to rethink biofuels policies (OECD-FAO, 2013)[2].

Whatever its alleged motivation (environmental concerns, increase energy security, improve balance trade or subsidize local farms), it is important to know price elasticities of fuels to correctly addressed. For example, considering Brazilian

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1 Some countries had similar public policies regarding to reduce oil dependence after oil shocks of 1970s, including Argentina, Costa Rica, Malawi, Sweden and Zimbabwe and decreased the interest with the fall of oil prices during 1980s. For more details see Johnson & Silveira (2014).

2 The effects of biofuels on deforestation and global hunger, lack of supply capacity and the monetary cost of those policies are in debate. In these major markets (Europe and US), biofuels do not have a good energy balance (total of fossil fuel energy needed to produce the biofuel). But, depending on the crop used the energy balance can change. When comparing ethanol from sugar cane with ethanol from corn, the former has energy balance six times larger than corn than the later. The same happens with CO2 reduction compared to gasoline. Ethanol from sugar cane can reduce CO2 emissions in 84%, while corn can reduce emissions in 30%. For more details see Goldemberg & Guardabassi (2010).

market, if a policy aims the reduction on gasoline consumption through increasing prices, it is important to answer some questions first: i) if gasoline prices are able to change consumption, what extent of change in prices is enough to reduce demand in 10%? ii) which price should be increased (decreased), once Brazilian gasoline is affected also by substitute prices?

Since knowing elasticities is important to propose public policies, how to estimate them properly is the next natural step. In this sense is important try to care about endogeneity problems caused by simultaneity between supply and demand. Without considering endogeneity problems, there is a downward bias (DAVIS; KILIAN, 2011), and estimation are toward to zero because of correlation between increases in demand and increases in prices, generating correlation between price and error term (price is endogenous).

Some methods have been used in the literature to address this problem, the most common is the Instrumental Variables (IV) approach. Regarding instruments for the gasoline prices, oil prices are the most used when we have a time series estimation. On the other hand, when estimations are based on panel data, an instrument that is "id invariant", which has no variance across panel, is redundant and not appropriated for the panel data estimation. Hence we did not use oil prices as instrument for gasoline prices and sugar prices as instrument for ethanol demand, they are panel invariant. In this study I use an approach close in spirit to Liu (2014) constructing instruments with purchase prices[3] of ethanol, gasoline and diesel, but excluding the prices of neighbors to avoid endogeneity issues.

The goal of this paper is to investigate the gasoline and ethanol elasticites, focusing on the changes led by the introduction of flex fuel cars in Brazil in 2003. The introduction of flexfuel cars increased the opportunity for consumers to arbitrage between these two fuels´ prices. Therefore, we expect to find evidence of greater demand substitution between these fuels. We hypothesized that the own and cross price elasticities of ethanol and gasoline in Brazil increased in their magnitudes after flexfuel cars. We investigated these hypotheses using monthly data from 2001m7

[3] Purchase prices are the price paid by consumers, price showed at gas stations' pumps.

to 2014m12. The inherent endogeneity problem is addressed with an Instrumental Variables (IV) approach in which we constructed instruments with temporally and spatially lagged purchase prices of ethanol, gasoline and diesel (excluding the prices of the nearest neighbors to avoid endogeneity).

This study makes several important contributions. By focusing on changes in price elasticities over time, we are able to consider the effect of an important change in the Brazilian market, the introduction of flex fuel cars. In addition, we improved the estimation of price elasticities using appropriate IVs to control for the simultaneity between prices and quantity. If estimation is not controlled for this problem, the biases is in direction to underestimate elasticities. Our IV results are larger in comparison with our OLS estimates and to previous estimates that did not control for endogeneity. Namely, our own price ethanol demand elasticities are around -1.5 and roughly 0.5 for the cross price elasticity. Likewise, gasoline demand elasticities are around -0.8 for the own price elasticity, and 0.1 for the cross price elasticity. Both demands showed an income elasticity around 0.8. Regarding the effects of flexfuel cars on the elasticities, using interacted time dummies to verify shifts on demands, the major shift was found from period 1 (2001m1 – 2005m6) to period 2 (2006m1 – 2010m6), while the parameters from period 2 to period 3 (2010m7 – 2014m12) had just small changes. The changes were in the expected direction, with increasing in substitution, namely, increasing in the cross elasticities prices. This increased substitution has positive implications for consumer welfare, given that consumers are now less susceptible to a price increase in any market. On the other hand, it has potential to make both markets more volatile.

The rest of this chapter is organized as follows. First, we review the previous literature on the demand for light fuels in Brazil and provide some highlights of the Brazilian light fuels market. We then describe the challenges of properly estimating ethanol and gasoline demands, with special attention to the endogeneity and instruments issues. Finally, this chapter concludes with a discussion of the results, and in the last section we present the final remarks.

1.2 BACKGROUND

1.2.1 Literature Review

Many studies worldwide with respect to demand for light fuels show gasoline as an inelastic good in the short and long run. Usually, long run elasticity tends to be larger because of a larger range of adjustment possibilities. These facts are in line with traditional microeconomics theory, once fuels have just a few alternatives in the short run, but these possibilities increase in the long run. For example, if gasoline price had an unexpected and permanent increase, the consumption in the following days probably would not change in a significant way, but with more time, consumers start to rethink their transportation strategies, generating larger changes in the demand.

Also from traditional microeconomics, demand for light fuels is modelled invariably using at least price and income as explanatory variables. Some studies, such as Burnquist & Bacchi (2002) and Cheung & Thomson (2004), do not use other controls and estimates demand using just these two variables. Two important surveys about gasoline demand are Dahl & Sterner (1991) and Espey (1998), and they showed a large range of econometric techniques used to estimate demand for light fuels, such as: time series, panel data, cross sections, instrumental variables and others. According to these surveys, estimated price elasticities are between $(-0.12; -0.44)$ in the short run and (-0.23;-1.05) in the long run. Income elasticities are between $(0.14; 0.58)$ in the short run and $(0.68; 1.31)$ in the long run. For a better view of other papers results we did a summary with the World average (surveys), one result for the US Market, one for Europe and the last results for the Brazilian Market (Table 1).

It is possible to see in Table 1 that Brazilian Market usually shows larger elasticities than US and Europe. This fact is due to income levels, preferences and markets specific features, as the presence of flex fuel cars in Brazilian Market. Santos (2013) estimated marginal effects for fuel market in Brazil using a DOLS estimator for the long run and a GMM´s Arellano Bond estimator for the short run. The effect of flex fuel on elasticities was small and/or insignificant (sample goes from Jul/2001 to Dec/2011 on quarterly basis). Freitas and Kaneko (2011) focused on effects of flex fuel cars on ethanol demand in Brazil, but carried out to estimate and explain the gasoline influence on ethanol demand, without taking into account ex-ante and ex-post changes due to introduction of flex fuel cars.

So far we are just highlighting the most important results in literature, without giving any motivation to calculate these elasticities. The main motivations to a better understanding of fuel market undergoing keywords such as energy security, long run oil shortage, the need of alternative fuels and environmental concerns.

It is well-known that oil is a finite resource, therefore, moving in a direction to be less dependent of it is a fundamental issue. The world proved reserves[4] of oil passed from 1041.4 thousand million barrels (tmb) in 1993 to 1687.9 tmb in 2013 (BP, 2014). Which represents reserves 62% larger than seen in 1993, and 27% larger than the one in 2003. Increases in the World proved reserves made the R/P (proved reserves/production) to be stable in values larger than 40 years since 1980. In 2013 the value of R/P was 53.3 years. It means that if nothing changes (technology, prices, consumption and discoveries), oil would last 53 years. This increase of R/P means that incorporation of proved reserves happened faster than increase in consumption (consumption increased 52% in the last 30 years, while proved reserves increased 62%).

This good news for energy security could mean a decrease in biofuels interest, however, environmental concerns have gained importance in biofuels motivations, becoming a catalyst for changes toward a low carbon economy. In this context, ethanol from sugar cane seems to be a good option in the medium run. Changes toward clean energy have been constrained by costs, roughly it is possible to say that there is a trade-off between clean and cheap energy: clean energy is not cheap and cheap energy is not clean. Sugarcane is in an alternative close in costs comparing

[4] Proved reserves can be calculated in different ways, but the most common is to use those quantities of oil that can be extracted with actual economic and engineering conditions. Therefore, increases in prices and/or better technology increase oil proved reserves.

Table 1 – References about Different Demands Estimations for Light Fuels

References[a]	Local	Time	Fuel Type	Short Run		Long Run	
				Price	Income	Price	Income
Dahl & Sterner (1991)b	World	1929- 1993	Gasoline	-0.24	0.80	-0.45	1.16
Espey (1998)[b]	World	1929- 1993	Gasoline	-0.23	0.30	-0.43	0.81
Burnquist & Bacchi (2002)	Brazil	1973- 1998	Gasoline	-0.23	0.96		
Alves & Bueno (2003)	Brazil	1974-1999	Gasoline	-0.47	0.12		
Roppa (2005)	Brazil	1979- 2000	Gasoline	-0.63	0.16		
Nappo (2007)	Brazil	1994-2006	Gasoline	-0.19	0.68		
Pock (2007)[c]	EU	1990-2004	Gasoline	(-0.02; -0.19)	(0.03; 0.23)	(-0.12; -0.84)	(0.16; 0.52)
Hughes, Knittel & Sperling (2008)	USA	1974-2006	Gasoline			(-0.30; -0.43)	(0.47; 0.54)
Serigati, Correia & Perosa (2010)	Brazil	2001-2009	Ethanol	(-1.20 and 2.20)	(-1.20 and 1.80)		
Farina et al. (2010)	Brazil	2001-2009	Ethanol	-1.23			
Souza (2010) [c]	Brazil	2001-2009	Gasoline	(-0.29; -0.37)	(0.07; 0.32)		
Souza (2011)[c]	Brazil	2001-2009	Ethanol	(-1.26; -1.82)	(0.20; 0.45)		
Freitas & Kaneko (2011)	Brazil	2003-2010	Ethanol	-1.43		-1.80	
Cardoso & Bittencourt (2013)	Brazil	2001-2011	Ethanol	-1.42	0.45	-3.30	2.82
Santos (2013)	Brazil	2001-2011	Ethanol	-1.52		-8.45	
Santos (2013)	Brazil	2001-2011	Gasoline	-0.78		-1.18	

Source: Author.
Notes: a) References are listed by year of publication; b) These papers are surveys, hence it was reported the mean of all studies; c) Some authors have many estimates, so it was reported the interval.

with oil and other alternative energies, besides to have a better energy balance than other crops used to produce ethanol, corn, for example. It is important to point out that, because, once biofuels are being supported by environmental arguments, but different crops have distinct energy balances. Different kind of Ethanol from different crops are very different regarding environmental point of view. In comparison with other crops, sugarcane is a better option regarding costs, land intensity and fossil balance related to corn (US production) and also regarding sugarbeet (Europe production) (GOLDEMBERG; GUARDABASSI, 2010). Hence, we can say that ethanol from sugarcane are "cleaner" than other crops, and also it has a smaller impact on competition with food (once it is less land intensive)(Table 2).

Whatever the motivation is (support local farms, environment, energy

Table 2 – Ethanol features by different crops.

	Sugarcane (Brazil)	Corn (US)	Sugarbeet (Europe)
Energy Balance[a]	8.1-10	1.4	2.0
Production Cost (/100 liters)	14.48	24.83	52.37
CO2 Reduction	84%	30%	40%
Production(liters/hectare)	6,741	4,182	5,510

Source: Goldemberg & Guardabassi (2010).
Notes: a) Energy output in a liter of ethanol over fossil fuel energy needed to be produced. So, with one liter of fossil fuel in Brazil it is possible to produce around seven times more ethanol than in the US. This difference is due to intensity in fertilizers of the US production compared to the Brazilian one.

security), knowing elasticities of ethanol and gasoline demand are key assets to a better policy choice. Policies aimed to increase local farmers´ demand for ethanol in Brazil and/or to reduce gasoline consumption should properly consider the role of both prices (ethanol and gasoline) on these demands. Income elasticities are also variables of interest, since they allow us to know how demands would answer to changes in income is an important variable to private and public sectors. More than these two key variables, Brazil also brings the importance of cross elasticities to fuel demand estimations. Depending on our answers for elasticities, public policies could be better designed in a sense to figure if demands are price sensitive, which price is more sensitive, whether income increases will be followed by increases in which fuel consumption, and in what extent.

1.2.2 Light Fuels in Brazil

Brazil is a special country regarding light fuels market. Because Brazilian fleet is composed by around 52% of cars that are able to use ethanol or gasoline, or any blend of these two fuels (flex fuel cars), there is a need to include the alternative fuel price to estimate both demands (ethanol and gasoline). Hence, not just the own price and income elasticities are important for Brazilian light fuel demand, but also the cross price elasticities. Studying changes and differences between Brazil and rest of world could help to understand the impact of future and current biofuels policies, so Brazil could be a mirror for what could happen in other countries regarding biofuels.

Biofuels policies in Brazil started supported by reduction on oil dependence, incentives to local farmers with the increase of ethanol demand and reductions of balance of trade problems by reductions of oil importations. During 1970s with oil crisis and increasing of oil prices, biofuels programs had a strong incentive in Brazil and in other countries. In the next decade, with the fall of prices, the incentives follow this fall. In Brazil, incentives on biofuels markets had a refresh in 2003 with flex fuel cars.

These policies resulted in one of the most cleaner energy matrices in the World, with more than 46% of primary energy production coming from renewable sources in 2013 (EPE, 2014), from which 19% of total primary energy coming from sugar cane products. The statement that ethanol is an economically feasible alternative for oil in Brazil should be better explained. Ethanol is competitive with gasoline in Brazil though a whole institutional arrangement which is mainly composed by:

i) Government Mandates - If nothing of hydrated ethanol is bought by flex fuel consumers, if they buy just gasoline, there is still 30% of anhydrous ethanol mixed in gasoline, which guarantees scale to producers;

ii) Car subsidies - Taxes on Industrialized Products (IPI)[5] are different between flex fuel cars and gasoline cars. The only situation when there are the same level of taxes for flex fuel and gasoline cars are for cars with 1000cc or less. For cars with larger engines (more than 1000cc) IPI tax is higher for pure gasoline cars than for flex fuel cars. It clearly increases potential demand for ethanol (SORDA; BANSE; KEMFERT, 2010);

iii) Subsidies directly on fuels - There is a higher tax burden on gasoline than hydrated ethanol in Brazil (JALES; COSTA, 2014). For the state of São Paulo, for example, taxes were roughly 21% of final price for ethanol and 42% for gasoline. The taxes are different across states, but, in all of them, gasoline is more taxed than ethanol.

Other interesting point is that ethanol is not homogeneously competitive across Brazilian states. One illustration can be done comparing purchase prices. The difference between the average purchase prices in the most expensive and in the cheapest state achieved 56% at ethanol market and just 13% at gasoline market. It illustrates a larger price dispersion in the ethanol regional markets. In some extent, these differences across states are due to logistic bottlenecks. In region North, for example, just a few states have ethanol prices competitive against gasoline ones. We constructed a map with the percentage of periods that gasoline is more competitive than ethanol[6] (Figure 1). The Figure 2 shows where are located ethanol production; the darker regions are the largest producers. Them, the five states in the middle of the figure are the largest producers, which together represent 86% of total production[7].

Consumption ratio between ethanol and gasoline (C_r) is defined here by the share of ethanol of each state in the Brazilian market (E_s), divided by gasoline

5 Acronym for "Imposto sobre Produtos Industrializados (IPI)" in Portuguese.

6 Ethanol has a lower energy content than gasoline, so to compare both prices we should multiply gasoline price by a constant of 0.7. Hence, if $Ethanol_{Price}/Gasoline_{Price} > 0.7$, it means that gasoline is more competitive. Otherwise, ethanol is more competitive.

7 All shares calculated for 2011 using National Agency for Petroleum, Natural Gas and Biofuels (ANP) available at ANP (2015).

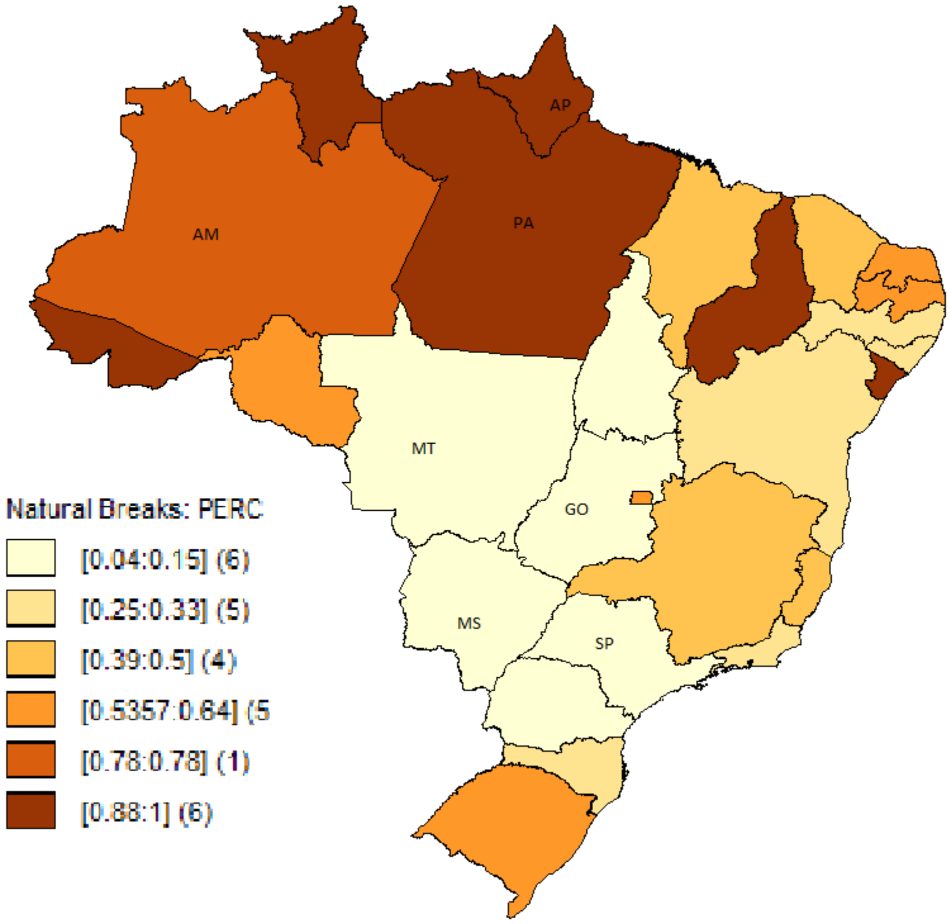

Figure 1 – Spatial distribution of periods that gasoline is more competitive.

Source: Authors.

participation (G_s). If (C_r) = 1, it means that the state´s consumption of gasoline and ethanol has the same pattern of consumption as the whole country. In the North (far from the largest consumer markets) the share (C_r) is 0.23, and hydrated ethanol consumption of those states are around 1.41% of total, while gasoline consumption is around 6.11% of total. Meanwhile, state of São Paulo[8] , the major producer and consumer has the share around 2.23, consuming 60% of ethanol and 27% of gasoline. These data show that even the Brazilian Government trying to sell the idea that ethanol could be an international commodity, it is competitive just in a few Brazilian

[8] The state of São Paulo is the most populous in Brazil (22% of total), richest in absolute terms(32.6% of Brazilian GDP) and the second in per capita income.

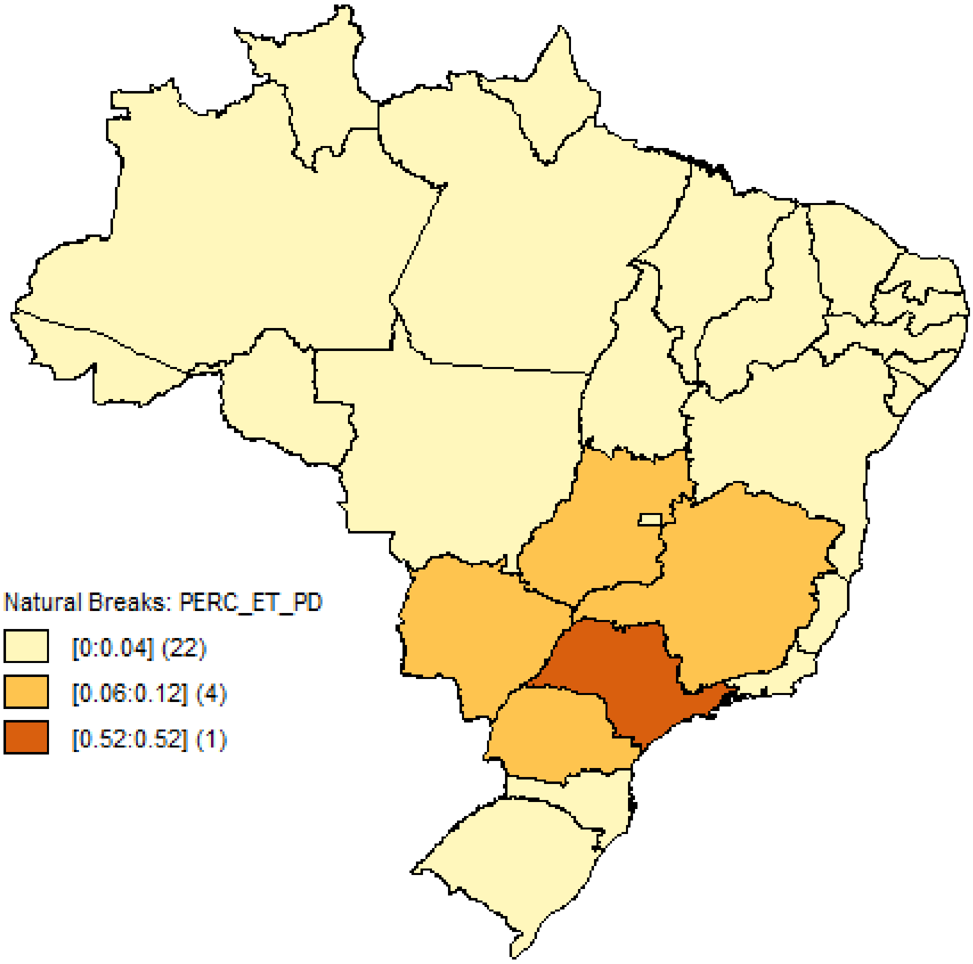

Figure 2 – Location of Ethanol Production.

Source: Authors.

states (close to producers), not in all of them.

1.3 HOW TO ESTIMATE THESE DEMANDS?

Once clarified why to study Brazilian fuels market demand, in the next step I will explain how to estimate these demands.

1.3.1 Literature Instruments

In order to achieve equilibrium, it is natural a back and forth between supply and demand curves. Regarding agricultural commodities for example, some increase in demand generates higher prices, higher prices increase supply, higher supply decreases prices, keeping other variables constant. Because price and quantity are equilibrium points of both curves and they are moving across time it could be a source of endogeneity, not allowing correct estimation of demand and supply curves. There is a possibility to say that fuel price is exogenous if there is an infinity elastic supply curve, not price sensible. Apparently it is not true even for large countries. Anderson (2012), for example, argues that the pricing strategies at gas station level is not a function of short-term shift demand, so US retailers follow the same strategy, arguing that gasoline price is constructed just as function of oil prices without feedback process between demand and supply.

The most usual is to treat price as an endogenous variable as did by Liu (2014) and Hughes, Knittel & Sperling (2008). The major bias source would be the positive correlation between demand and prices, biasing error and creating a toward zero bias. In a simple equation, endogeneity could be visualized as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + \mu,$$
$$E(\mu) = 0, \quad Cov(x_j, \mu) = 0, \quad j = 1, 2, ..., k-1. \tag{1.1}$$

Note that the exogenous variables ($Cov(x_j, \mu) = 0$) go until x_{k-1} because x_k is our endogenous estimator. Be endogenous in an econometric sense means to be correlated with error term and not be generated out of the model. This feedback between model and variable makes impossible to properly verify the marginal effects, in other words $Cov(x_k, \mu) \neq 0$ is not a problem just for β_k, but for all β_j. We cannot consistently estimate Equation 1.1 using OLS.

In some estimations of gasoline demand is possible to find results inconsistent theoretically, as positive price elasticities or inelastic total price demands (NOLL, 2013). The major reason for that is that demand increases are followed by price increases, creating a contemporaneous positive correlation between prices and demand, biasing estimators. In order to solve that, IV approach indicates that we need at least one **valid instrument** (z_1) for each endogenous variable (WOOLDRIDGE, 2010, p. 89). Valid instruments have to assure two features: i) an exogenous instrument ($Cov(z_1, \mu)) = 0$); ii) a different from zero correlation between z_1 and x_k. Frequently, the practical concern is a tradeoff between relevance and exogeneity of instruments. The relevance of instrument is usually interpreted as different from zero partially correlation between instrument and the endogenous variable, once the coefficient of z_1 in x_k equation, θ_1, need to be different from zero:

$$x_k = \delta_0 + \delta_1 x_1 + \delta_2 x_2 + ... + \delta_{K-1} x_{K-1} + \theta_1 z_1 + r_K \tag{1.2}$$

The Equation 1.2 is considered as the first stage of an IV approach and its estimation should have $E(r_k) = 0$ and r_k uncorrelated with its explanatory variables. Regarding our instruments, for instance, it is easy to find significant coefficients, so we have strong instruments. The major problem is to find instruments that are really exogenous.

According to the literature, it is important to have in mind if database is a time series or a panel data. This feature makes a large difference for the instrument choice. Are international sugar prices good instruments for ethanol prices[9]? Depending on the type of database, for time series, the answer would be yes, but for panel data with time-effects, the answer would be negative. In a panel data with time effects, there is no reason to include an instrument with no variation intra-panel, this instrument will be cancelled, redundant, with time-effects. The same explanation is used to justify why international oil prices are not a good instruments for gasoline prices at state level panel data.

Following the literature in the attempts to find good instruments, Liu (2014) argues that the prices of other states can be used as instruments. They are correlated by supply side, being a good instrument for prices in each state, so the author used average price of non adjacent states. This approach is close

[9] In Brazil the mainly crop used to ethanol production is sugarcane and there is a little arbitrage choice regarding the firms production, where some firms can change the production between sugar and ethanol. Hence, the sugar price is relevant for the ethanol supply.

in spirit to the use of some lagged spatial variable, but in spatial econometrics is more common to use information of closer states not the information of the most distant ones. The principle is that closer places should explain more than distant ones, following the first law of geography of Toble[10].. In Liu (2014), because of endogeneity concern, the way to procedure the weighted matrix is the inverse, more distant places are less likely to have endogeneity, so first order neighbours entered in .

1.3.2 Our Instruments

In the hard task of finding a good instrument for prices, a common attempt would be to get some instrument candidates from the supply side. This is the motivation to use oil prices as instrument for gasoline demand and sugar prices for ethanol demand (in a time series approach). Oil prices are one of most important costs for gasoline and the sugar price is an important component in the opportunity cost to produce ethanol.

Here we used **purchase prices** of diesel, gasoline and ethanol to construct our instruments. Therefore, our instruments are average prices where just the prices of non-adjacent states are computed. We depart from a matrix of Ones (27 x 27) and reduced a Queen-1 matrix (27 x 27) from that. It generates a matrix where the neighbors are being considered, and the only problem is that the principal diagonal is full of ones (also being considered), so we still diminished an Identity matrix from that and row standard the results to generate our **Instruments Matrix (IM)**. If the matrix is resulted from a Queen-1 it will be called by IM. In matrix language we define:

$$\mathbf{W} = (w_{ij}) \quad where \quad w_{ij} = \begin{cases} 1 \quad if\ states \quad are \quad neighbours \\ 0 \quad if \quad i = j \\ 0 \quad if\ states \quad are \quad not \quad neighbours \end{cases} \tag{1.3}$$

[10] Toble's first law of geography: "Everything is related to everything else, but near things are more related than distant things." (TOBLER, 1970)

$$\mathbf{One} = (1) \qquad \mathbf{I} = (i_{ij}) \quad where \quad i_{ij} = \begin{cases} 1 & if \quad i = j \\ 0 & if \quad i \neq j \end{cases} \tag{1.4}$$

Remember that all these three matrices (**W**, **One** and **I**) are 27 x 27. Then, our **IM** matrix (also 27 x 27) is [11]

$$\mathbf{IM} = \mathbf{W} - \mathbf{One} - \mathbf{I} \tag{1.5}$$

After that I row standard **IM** to finally obtain IM.

Finally the price matrix (27 x 162) is pre multiplied by IM matrix to construct our price instruments.

Regarding positive contemporaneous correlation between demand and prices, I also used lagged prices trying to achieve more exogenous instruments. The intuition here is that the farther temporally is the variable, the lower is the probability that this variable is correlated with error term in the mainly equation (second stage - Equation 1.7).

Because gasoline in Brazil is a blend (27% anhydrous ethanol + 73% gasoline) there is also the possibility of hydrated ethanol prices being endogenous in gasoline demand: increases in gasoline demand increases demand for anhydrous ethanol, which increases prices of anhydrous and hydrated ethanol. We believe that neglecting this problem leads to toward zero bias in ethanol prices in the gasoline demand, presenting insignificance in ethanol price estimated parameters. Hence, we also tested endogeneity of ethanol prices on gasoline demand.

1.3.3 Model and Summary Statistics

Around the world is common to include population as a control for fuel demand. But it is not a good option to capture the real fleet effects in Brazil. Because it is a middle income country, the **fleet** has been changing in relation with population. In 2000 there were 8.4 people/vehicle, eleven years later this ratio was around 4

[11] 27 is the N dimension, number of states in Brazil, and 162 (regarding price matrix) is the temporal dimension, 162 months.

people/vehicle. Just to compare, US has a ratio around 1.25 people/vehicle, losing just for Monaco and San Marino[12]. We used the Denatran database to construct our fleet variable.

The other variables used to estimate fuel demand are the prices (own prices and substitute prices) and income proxies. Then, the basic model is:

First Stage :

$$P_{1it} = \delta_0 + exogenous + instruments + \upsilon_{it} \tag{1.6}$$

Second Stage :

$$\begin{aligned} Q_{it}^{j} &= \beta_1^j \hat{P}_{1it} + \beta_2^j P_{2it} + \beta_3^j Inc_{it} + \beta_4^j Fleet_{it}^j \\ &+ regional\ effects + time\ effects + \varepsilon_{it} \\ \\ j &= gasoline,\ ethanol; \qquad i = 1, 2, ..., N; \qquad t = 1, 2..., T. \end{aligned} \tag{1.7}$$

In the Second Stage (Equation 1.7) the regional effects are dummies to capture fixed effects of states. The time effects are dummies to capture fixed effects of each month.

The Equations 1.6 and 1.7 are used to estimate both demands. The database is a panel data (NT) where N varies from 1 to 27 (number of sates in Brazil) and t varies from 1 to 162 (being 1 related to July/2001 and 162 to Dec/2014), so we have a panel with 4374 observations ($N.T$).

The quantities in the data set (Q_{it}^{j}) are the hydrated ethanol and gasoline-c sold at gas stations in barrel of oil equivalent quantities. Gasoline prices and ethanol prices are the monthly weighted averages of consumer prices provided by National Agency for Petroleum, Natural Gas and Biofuels (ANP). The income proxy used here was a state-level tax (ICMS[13]). We are using ICMS instead of electrical consumption

12 The data of US, Monaco and San Marino is available at World Bank Database. For Brazil see the National Motor Vehicle and Traffic Department Database (Denatran).

13 Abbreviation in Portuguese for *Imposto sobre Circulação de Mercadorias e Serviços*. It is important to clarify that we did not use common income variables, per capita GDP, for example,

proxy for two reasons: i) do not input a fix effect;[14]. ii) IMCS is a better proxy than energy consumption mainly because of technological changes towards energy-savings and environmental concerns would likely decrease the correlation between them (GDP and energy consumption). The summary statistic are in Table 3.

We also have purchase prices of ethanol, gasoline and diesel, and these prices

Table 3 – Summary statistics of the main variables

Variable	Obs	Mean	Std. Dev.	Units
Ethanol Prices (P_{eth})	4374	1.841	.426	R$
Gasoline Prices (P_{gas})	4374	2.525	.381	R$
Diesel Prices (P_{die})	4374	1.894	.44	R$
id	4374	14	7.79	States
time (months)	4374	578.5	46.77	July/2001 to December/2014
Amount Ethanol (bep)	4374	103794.8	332049.6	barrel of oil equivalent
Amount Gasoline (bep)	4374	468475.5	707858.9	barrel of oil equivalent
Income (Inc)	4291	688526.2	1304074	R$
Fleet ($Fleet$)	4374	2.67e+07	5680398	number of cars
Inflation Index (IPCA)	4374	1.468	.225	Index (July-2001 = 1)
Gasoline Prices (IM-1)(P_{gas}_IM1)	4266	2.162	.322	R$
Ethanol Prices (IM-1)(P_{eth}_IM1)	4104	1.539	.372	R$
Diesel Prices (IM-1)(P_{die}_IM1)	4266	1.552	.386	R$

Source: Author.

are weighted by the sales of each gas station and are provided by National Agency for Petroleum, Natural Gas and Biofuels (ANP). We will use these prices as instruments for gasoline and ethanol price. Trying to have more exogenous instruments we will use similar strategy as Liu (2014), using just the prices of non-neighbors as instrument. So, "IM1" is reference to price constructed from **IM-1** matrix of non-neighbors. The IM-2 prices are used just for consistency tests (not reported in Table 3.

because in Brazil these variables are not available for all states on monthly basis.

[14] Energy consumption on monthly basis is available just at region-level (dividing Brazil into 5 regions and not into 27 states) which input a fixed effect by region when we tried to construct the variable by state.

1.4 RESULTS

1.4.1 Preliminary Results

Regarding endogeneity issues we should do two basic questions:

i) Is there an endogeneity problem?

ii) Is there a valid instrument?

The first question we tried to answer using the Durbin-Wu-Hausman approach (testing the consistency through differences between OLS and 2SLS estimators) and using control function approach (including residuals of first stage regressions into second stage). Using both approaches, own prices are endogenous in ethanol and gasoline demands, as expected. We also have an intuition that ethanol price is endogenous in the gasoline demand, so shocks on demand for gasoline could be transmitted to ethanol prices by anhydrous ethanol channel. This channel causes negative contemporaneous correlations between ethanol prices and gasoline demand, when we would expect positive correlations. Hence, we also test the endogeneity of ethanol prices on gasoline demand. Another way to achieve the same result is using the residuals of the first stage (Equation 1.6) in the main regression (Equation 1.7). If the coefficient of the estimated residuals is different from zero, we also have endogeneity problems (WOOLDRIDGE, 2010, p. 130). Using both approaches, ethanol price was endogenous in both demands, and gasoline price is endogenous in its own demand.

What to expect from results? First of all, we would expect negative own prices elasticities, since we are estimating a demand curve and not a supply one. Regarding all other key parameters (alternative fuel price, income and fleet) we expected positive elasticities for both fuel demands. For example more income, fleet or alternative fuel price, more demand for gasoline, ceteris paribus. We also expected more elastic prices and cross price parameters for ethanol demand than for gasoline one. The intuition for that is because ethanol demand is basically composed by flex fuel fleet (higher arbitrage degree)[15].

Table 4 shows ethanol as an elastic good, which is a different feature from

Table 4 – Ethanol Demand Estimations using Different Instruments

	Gasoline Purchase Prices	Ethanol Purchase Prices	Diesel Purchase Prices
Fleet	0.546***	0.728***	0.469***
	(4.85)	(5.87)	(4.39)
Pg	0.463***	0.510***	0.549***
	(3.58)	(4.03)	(4.15)
Income	0.810***	0.746***	0.870***
	(45.37)	(39.28)	(51.75)
Pe (IM-1)	-1.494***		
	(-16.35)		
Pe (IM-1)		-1.645***	
		(-17.73)	
Pe (IM-1)			-1.542***
			(-16.85)
_cons	-9.232***	-11.55***	-8.691***
	(-4.93)	(-5.59)	(-4.86)
N	4156	4003	4156

Source: Author.
Notes: a) On top of each column is indicated which instrument was used; b) t statistics in parentheses; c) First stage is not reported here, but instruments had highly significant parameters; d) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

fuel market abroad. Basically all results, including some surveys, found fuel market as a price inelastic good ($E_p < |1|$) (considering gasoline market). It seems that ethanol market, mainly because possibility of arbitrage regarding flex fuel cars, became a fuel market with less inelastic price. Due to the used log-linear functional form, coefficients can be interpreted directly as elasticities, so ethanol has elasticities around (-1.5) for the Brazilian market and these results are at the top range of other elasticities estimations from the literature. Literature range is between (-1.5) and (-1.2), being the higher values for the most recent papers (SANTOS, 2013; FARINA et al., 2010; CARDOSO; BITTENCOURT, 2013; FREITAS; KANEKO,

15 Since 2006 there is no pure ethanol cars production, therefore the proportion of ethanol fleet is around 2% and tends to be zero in the long run.

2011).

Regarding income elasticity estimations, we found values slight smaller than one, indicating that expansion of income has a large impact on ethanol demand. These income elasticities' results are larger than results from US and Europe. Hughes, Knittel & Sperling (2008)(USA) and Pock (2007)(Europe), for example, did not find income elasticities larger than 0.52, even considering long run parameters. This follows the intuition that increases in income should have smaller impact in higher income level countries.

Other important point is the results' robustness regarding instruments choice. All three instruments performed very close. About the relation between the two prices, cross prices elasticities on ethanol demand were around one third than ethanol prices' effects. This shows that ethanol demand is more sensitive to its own price than gasoline price. In other words, ethanol demand is more sensible to ethanol prices than to gasoline prices (Table5).

In the gasoline demand estimation (Table 5) all instruments also performed closely. The main difference is that in gasoline demand we used instruments for gasoline price and for ethanol price (substitute good is also endogenous because of anhydrous portion into gasoline[16]). Therefore, in the second column estimates we have multicollinearity because ethanol purchase prices are used for construction of both prices (ethanol prices and gasoline prices). This is likely the reason for the coefficient of the ethanol price not being significant.

Regarding own elasticities (gasoline prices' parameters) we found higher elasticities than international evidence, probably because of a combination between higher arbitrage (flex fuel cars) and a smaller income in Brazil. Comparing with Brazilian evidence, we found parameters close to Santos (2013)($E_p = -0.78$), for example. The elasticities of gasoline demand were roughly half of the ethanol elasticities. This indicates that ethanol demand is more price sensitive than gasoline price. It is an expected result because of ethanol demand is almost totally composed by flex fuel cars (consumers have choice to change fuel type any time), while gasoline

[16] Gasoline C in Brazil is a blend with roughly 30% of anhydrous ethanol and 70% of gasoline.

Table 5 – Gasoline Demand Estimations using Different Instruments

	Gasoline Purchase Prices	Ethanol Purchase Prices	Diesel Purchase Prices
	lnqgas	lnqgas	lnqgas
Pe	0.105*	0.0884	0.103*
	(1.98)	(1.72)	(1.99)
Income	0.801***	0.801***	0.803***
	(136.59)	(141.69)	(142.26)
Fleet	0.359***	0.356***	0.347***
	(9.92)	(10.34)	(10.05)
Pg (IM-1)	-0.871***		
	(-10.39)		
Pg (IM-1)		-0.900***	
		(-11.15)	
Pg (IM-1)			-0.934***
			(-11.49)
_cons	-3.111***	-3.040***	-2.881***
	(-5.13)	(-5.28)	(-4.99)
N	4003	4003	4003

Source: Author.
Notes: a) t statistics in parentheses; b) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

demand is part flexfuel, part not.

Income parameters were almost the same for ethanol and gasoline demand estimations, then, the impacts from income increases would be roughly the same for ethanol and gasoline demands.

1.4.2 Are the elasticities constant? The role of flex fuel cars

Most of the studies in the literature uses log-linear specification for light fuel demand estimation. In addition to the facilities to interpret directly the parameters as elasticities, come also the imposition that elasticities are constant for the whole sample. We will relax this not with a different specification, but using sub-samples to allow different price and cross price elasticities along the time. It will also allow differences at income elasticities, but it was around 0.8 for both demands along our sub-samples.

We would expect higher cross elasticities after the introduction of flex fuel cars and the current literature confirms that. But we believe that there are mixed effects causing this higher elasticities: i) the older literature does not take into account for endogeneity, thus tends to underestimate elasticities (as explained earlier, the literature does not take into account for endogeneity and has a toward zero bias into these demands); ii) flex fuel cars introduction, tending to increase arbitrage between both fuels, increasing cross price and own price elasticities, becoming fuel more price sensitive. Hence, in order to account for changes in elasticities over time, we interacted price and cross price parameters with time dummies.

Time dummy variables regarding 2006m1 and 2010m7 split our sample into 3 equal periods. The justification to use 2006 and not 2003 as the starting point(the beginning of flexfuel cars production) is because flexfluel fleet was so small in 2003 that would not be enough to change elasticities. The proportion of flexfuel cars in the first period went from zero to 8% of total cars. In the end of the second period (2010) flex fuel cars reached 37%, and in the end of our sample this proportion was around 52%. Another important event in 2006 was that flexfuel cars production exceeded gasoline cars' production. Table 6 shows the results of the estimated coefficients after re-parametrization.

Ethanol price and cross price elasticities had a large increase from period 1 (2001m1-2005m12) to period 2 (2006m1-2010m6), and the changes for period 3 were small. Other important result is that in the period 1, cross price coefficient of ethanol demand shows an insignificant result, but in the next two subsequent periods it showed significant results. The gasoline demand had the same behavior, with a larger increase in elasticities from first to second period and just a little change from second to third period. Again, the cross price coefficient was not significant in the first period, becoming significant in the following periods (Table 6).

In period 1 (without flexfuel cars), with the lack of power of substitution between two fuels, parameters of cross elasticity were not significant, in the next two periods the signals became significant and with expected signals (Table 6).

Regarding possible critics regarding the thresholds used in dummy variables,

Table 6 – Price Elasticities Across Time

	(1) Ethanol Demand	(2) Gasoline Demand
Ep(etha) - time - 1	-0.690***	0.00107
	(-5.71)	-0.01
Ep(etha) - time - 2	-3.136***	0.258***
	(-21.61)	-3.35
Ep(etha) - time - 3	-3.398***	0.334***
	(-17.15)	-3.38
Ep(gas) - time - 1	0.206	-0.675***
	-1.55	(-6.80)
Ep(gas) - time - 2	1.327***	-0.988***
	-9.45	(-10.40)
Ep(gas) - time - 3	1.281***	-0.912***
	(8.00)	(-8.51)
N	4003	4156

Source: Authors.
Notes: Intervals: Time 1: 2001m1-2005m12; Time 2: 2006m1-2010m6; Time 3: 2010m7-2014m12.

we constructed around 90 regressions for each demand consisting on subsample of 3-year observations. Because it is a moving window sample, observations in the first subsample goes from 2001m7 to 2004m6; the second goes from 2001m8 to 2004m7, and so on. The most interesting result of this approach was that we can note exactly when the cross price elasticites became significant, when the confidence interval of cross price elasticities is above zero. It happens with subsamples from 2006m7 to 2009m6 for the ethanol demand (Figure 3) and from 2007m1 to 2009m12 for gasoline demand (Figure 4).

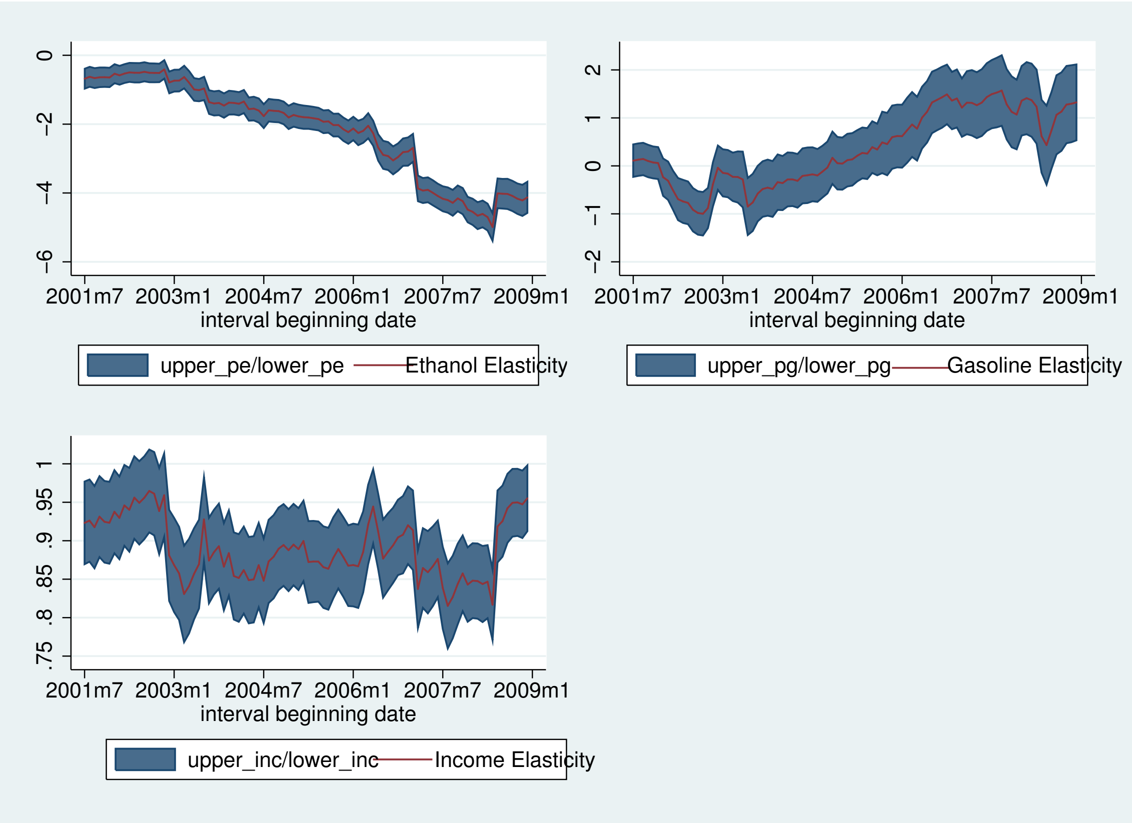

Figure 3 – Ethanol Demand Coefficients

Source: Author. Notes: a) It is a moving window estimation, which moves forward 1 month in each new estimation; b) Each subsample has 36 observations.

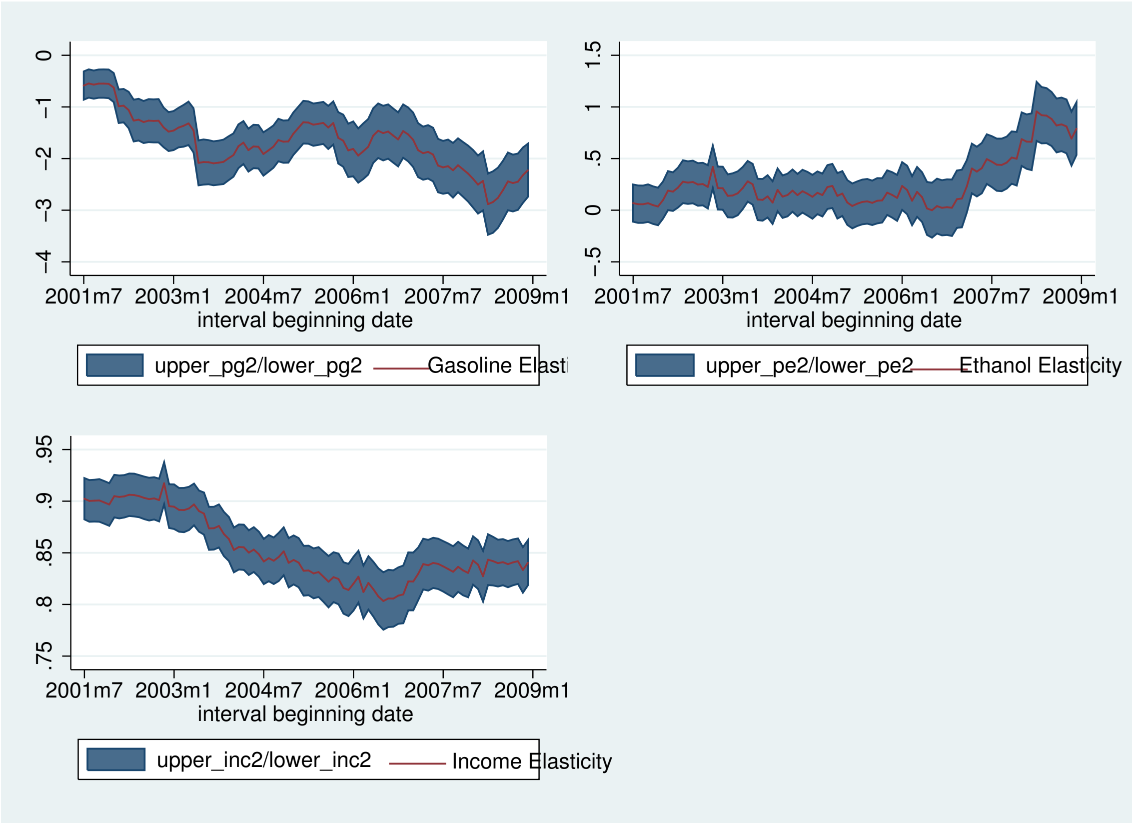

Figure 4 – Gasoline Demand Coefficients

Source: Author. Notes: a) It is a moving window estimation, which moves forward 1 month in each new estimation; b) Each subsample has 36 observations.

1.5 FINAL REMARKS

Using purchase prices of non-neighbors as price instruments, we estimated the ethanol and gasoline demands. The most important findings were:

i) Ethanol ($Ep = -1.5$) and gasoline ($Ep = -0.8$) are price sensible, with higher elasticities than the elasticities in the US and Europe, for example. Hence, public policies driven by prices could be applied;

ii) Cross elasticities were significant in both demands, so ethanol and gasoline are actually complementary goods for the Brazilian Market and any public policy addressed to one market should take into account spillovers to the other market. It is clear that this change occurred after the introduction of flex fuel cars. It is possible to say that because in the fist subsample (small or zero flex fuel fleet) the cross price elasticities for both demands were not significantly different from zero and in the second period they became significant and with the positive expected sign;

iii) Using a moving window sample we reached a most accurate threshold from where the cross elasticities were significant. Namely it happens from 2006m7 for ethanol and from 2007m1 for gasoline;

iv) After the introduction of flex fuel cars, there were an increase in the own price elasticities in both demands, meaning an increasing in arbitrage for fuel demands;

v) Accounting for endogeneity in both demands generated larger elasticity coefficients for gasoline (comparing to previous literature addressed to Brazilian market), but quite similar results regarding ethanol demand.

Our price elasticities' estimations are just an indicative of how prices could respond for shocks. It is possible that the nature of the shock is important for demand responses. For instance, Coglianese et al. (2015) argue that taxes changes could have a larger effect than regular changes. In other words, 10% reduction on demand caused by oil costs would be a smaller reduction on demand than the same increase driven by taxes. The reasons for that would be the exposition of taxes changes in the media and the persistence of shocks by taxes, media exposition and tax aversion by consumers.

As the most demand studies, our results are exposed to the Lucas Critique. Even being a short run estimate, the accuracy of the model depends on the extent of changes, severe shocks increasing the possibility of parameters change and become harder to make predictions.

ACKNOWLEDGMENTS

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2 PRICE VOLATILITY TRANSMISSION FROM OIL TO ENERGY AND NON-ENERGY AGRICULTURAL COMMODITIES

Abstract

The first transmission linkage between oil and agricultural markets is from production side, where fertilizers are an important input and they are oil-intensive. Recently, biofuels likely increased integration between these markets, creating an extra linkage on the demand side. This higher integration likely increases the price volatility transmission, which can increase uncertainty in agricultural markets. Hence, this chapter aims to investigate the integration behavior between these markets, checking if there are differences in price volatility transmission from oil to two groups of agricultural commodities: i) energy agricultural commodities (EAC), used in biofuels production; ii) non-energy agricultural commodities (NAC), not used in biofuels productions. In order to do that, I used Mgarch models on monthly basis and found that price volatility spillovers became stronger for both groups (EAC and NAC), but with opposite directions. In other words, quasi correlations between EAC returns and Oil returns moved in the same direction over time, and in 2008 this conditional correlation became more positive. On other hand, quasi correlations between Oil and NAC returns moved in opposite direction, and during Financial Crisis they became more negative. Changes in market integration implies in revision of bond traders strategies regarding the use of agricultural commodities for portfolio diversification and for public policies issues regarding public policies addressing to mitigate volatility transmission.

Keywords: oil, agricultural commodities, biofuels, volatility transmission, mgarch.

Resumo

O primeiro link de transmissão entre o petróleo e as commodities agrícolas é pelo lado da oferta, os fertilizantes são um importante insumo e eles são intensivos em petróleo. Recentemente, os biocombustíveis provavelmente aumentaram a integração entre esses mercados por conta da criação de um link extra pelo lado da demanda. Essa maior integração teria aumentado a transmissão de preços entre esses dois mercados, assim como a transmissão de volatilidade, o que aumentaria a incerteza no mercado de commodities agrícolas. Dessa forma, esse capítulo objetiva investigar a transmissão de volatilidade entre esses dois mercados, observando se essas transmissão se dá de forma diferente de acordo com o grupo de commodities agríciolas. A saber, as principais commodities agrícolas foram dividas em dois grupos distindos: i) Energy Agricultural Commodities (EAC), que são aquelas commodities que além do link pelo lado dos fertilizantes, também tem o link pelo lado da demanda por biocombustíves; ii) Non-Energy Agricultural Commodities (NAC), que são as commodities agrícolas que possuem apenas o link por conta dos fertilizantes. Pra medir essa transferência, foi usado um MGARCH em bases mensais. Os resultados indicam que existem spillovers na transmissão de volatilidade entre os três índices (Petróleo, NAC e EAC). Esses spillovers indicam que as quasi correlações entre os retornos dos índices NAC e Petróleo foram negativas, enquanto que as quasi correlações entre EAC e Petróleo foram positivas. Outro resultado interessante é que essas correlações se tornaram mais fortes (mais positiva para EAC e Petróleo e mais negativa para NAC e Petróleo) durante a Crise Financeira. Essas mudanças na integração dos mercados indicam para revisão das estratégias de diversificação dos investidores e das políticas públicas com a finalidade de diminuir a volatilidade dos mercados.

Palavras-chave: petróleo, commodities agrícolas, biocombustíveis, transmissão de volatilidade, mgarch.

JEL: G13, Q14, Q42, Q02.

2.1 INTRODUCTION

Volatility in agricultural markets increased substantially after 2006. Historically, price-demand inelasticity for agricultural commodities is a primary reason to explain high volatility in agricultural prices. It means that quantity demanded are less price responsive and supply shocks are accommodated mainly by prices. If price inelasticity is a well-know feature of food demand, which historically increases its price volatility, it can not be pointed as a reason to recent increases in volatility. Which new factors could be increasing the volatility? The literature indicates that the main contributors could be:

i) Financialization: Rising in trading volume assets brought larger price variations (FLEMING; KIRBY; OSTDIEK, 2005)[1]. Increases on agricultural commodities traded as financial assets could increase price volatility;

ii) American monetary policy: Increasing demand for financial assets, increasing price volatility (FRANKEL, 2006; ASKARI; KRICHENE, 2008; NAZLIOGLU; ERDEM; SOYTAS, 2013);

iii) Macroeconomic factors has increased demand for commodities from China (GILBERT, 2010);

iv) Biofuels: which would marginally increase demand for agricultural commodities, increasing price volatility (BABCOCK, 2012; CIAIAN et al., 2011; SERRA, 2011; HOCHMAN et al., 2012).

Obviously these factors are not consensus in economics (like almost everything else), but they are the most frequent factors to explain prices volatility in agricultural markets.

Agricultural and oil markets have an older and well-known linkage given by input markets because fertilizers are oil-intensive. Therefore, we can say that

[1] In this case, correlation between crisis periods and high traded assets would be captured by traded volume (FLEMING; KIRBY; OSTDIEK, 2005).

oil prices are one of the agricultural prices determinants in both, short and long run (SERRA; ZILBERMAN, 2013). Hence, it is expected that there is some price volatility transmission between oil and agricultural commodities markets.

Part of the empirical literature about commodities prices believes that biofuels have not a significant effect in rising agricultural commodities prices. It is argued that biofuels represent a small market share that cannot cause large demand shifts (AJANOVIC, 2011). On the other hand, part of the literature claims that even a little market share in presence of inelasticities it is enough to shift prices, the price effects are leveraged by demand inelasticities. Even though biofuels are not a consensual reason to explain volatility increases in agricultural markets [2], we found more empirical evidence that they have a role on agricultural commodities prices, as suggested by Babcock (2012), Ciaian et al. (2011), Serra (2011) and Serra & Zilberman (2013). The existence of this extra linkage produced by biofuels is the starting point for our research question.

The research question is: are there differences in price volatility transmission from oil to agricultural markets in the presence and absence of this extra linkage by biofuels?

In order to answer that, the most traded agricultural commodities will be divided into two groups: **i) Energy Agricultural Commodities (EAC) – sugar, corn and soybeans; ii) Non-Energy Agricultural Commodities (NAC) – rice, coffee, sunflower, cotton and wheat**. The main idea is to test volatility spillovers among these three indexes (Oil, EAC and NAC). More specifically the goals are twofold: i) to test if there is transmission of price volatility from fossil markets to agricultural markets; ii) to test if there are differences between price transmission of agricultural commodities with direct energy link (soybeans, sugarcane and corn) and agricultural commodities with just the fertilizer's link (coffee, rice, cotton, sunflower and wheat).

Conventional Ordinary Least Squares (OLS) approach cannot be applied in

2 Ajanovic (2011), for example, says that there is no significant impact of biofuels on feedstock prices.

order to answer those questions, and the reason is the assumption that residuals are homoscedastic underlying the OLS. In a 'homoscedastic world' there is no reason to model volatility, it is just a constant. To overcome this assumption ARCH and GARCH models can be used in a multivariate scenario (MGARCH)[3], which will allow to model volatility including cross volatilities as part of explanation[4].

Using monthly data from January/1989 to May/2013 (293 observations)[5], the results show larger quasi-correlations parameters for EAC than NAC in price equations, suggesting that oil drives more volatility to commodities with biofuels linkage. Looking at returns equations, EAC has positive quasi-correlations and NAC has negative quasi-correlations, suggesting that Oil and EAC returns moves in the same direction and Oil and NAC returns move in opposite directions.

This chapter has, besides this introduction, a section for literature review about volatility transmission and some facts motivating our study, a section to explain the econometric approach, followed by data and results. Finally, last section is dedicated to the final remarks and comments.

2.2 SOME FACTS AND LITERATURE REVIEW

The majority of studies about commodity prices uses first moment of regression (mean equation). Although second moment empirical models (volatility equation) are less studied, volatility is a central variable to risk measurement. The literature on finance was the first area in economics to realize this importance and used second moments in asset pricing models, hedging and risk management analysis. This literature associates more volatility with higher risks and more risks requiring a more profitable expected outcome to be accepted (BAUWENS; LAURENT; ROM-

[3] Multivariate Generalized Autoregressive Conditional Heteroskedasticity.
[4] In this family of models it is allowed that volatilities in one variable explain the volatility of other variable.
[5] Monthly spot prices of eight most traded agricultural commodities can be easily found in several databases as Ipeadata, Food and Agriculture Organization (FAO) and Chicago Board of Trade (CBOT).

BOUTS, 2006, p.79).

Oil is frequently pointed as one of the most volatile commodities. According to Regnier (2007), it is more volatile than 95% of products sold by US domestic producers. This high volatility likely has microeconomic implications, as "persistent underinvestment in conservation technology"[6] and optimal requirements choice in industry, and also macroeconomic implications, such as instability in the public finance of economies with high oil dependence (both export dependent and import dependent). It can explain why there are so many policies addressed to reduce energy price volatilities for consumers and industry. In Brazil, for instance, most of oil refineries belong to Petrobras (government is the major shareholder) that transfers price for consumers in a smoothed way. Around the world, public stocks are also used in attempt to reduce volatility. Biofuels defenders argue that investment in energy alternatives could reduce oil volatility. It is correct, but this reduction is not verified because biofuels are just a small market share (compared to oil) and having so much government intervention. The part of government intervention increasing volatility occurs when government artificially increases integration between oil and biofuels market by blend mandates, for example.

Agricultural commodities are recognized by short term inelasticity in both demand and supply curves. Once the people are not suffering by hunger, increases on demand are caused by increases on population. It is not hard to see that this increase does not happen by jumps, it is a gradual and slow increase. On the other side, supply of an agricultural commodity takes, at least, one harvest to be changed. Therefore, when exogenous shocks happens, a climate problem (unexpected frost, for example) dropping supply, once adjustment by quantities is not possible, all effects need to be accommodated by prices (RODRÍGUEZ; RODRIGUES; SALCEDO, 2010).

The period 2006-2008 is called in agricultural price literature by Food Crisis.

[6] High price volatilities are associated with high market risks. Hence, for energy prices, high volatility is pointed as a cause of low investment in energy conservation and energy alternatives (REGNIER, 2007).

Recently (2011-2012), agricultural prices have been rising again (Figure 5). But in both periods there were more than price increases, there was also increasing on prices volatility. Since market inelasticity is a historical characteristic of agricultural markets, we should think in new reasons to understand these recent periods of increasing price volatility, or to suppose that recently the curves became even more inelastic.

Agricultural-oil market integration is pointed as a reason for increases in agricultural prices volatility. A first, and older reason, for this integration is that fertilizers' production is oil-intensive, which implies in some degree of integration by transfer of costs. Second, and more recent reason, is that there is an extra linkage provided by biofuels. This extra linkage is used to divide commodities into two groups in this paper: i) energy agricultural commodities (EAC) – extensively used in biofuels production (sugarcane, corn and soybeans); ii) non-energy agricultural commodities (NAC) – not extensively used in biofuels production (rice, coffee, sunflower, cotton and wheat). It is our belief that this increase in the transmission channel increases volatility in agricultural markets because oil price is more volatile than agricultural prices.

This volatility transmission (oil-agricultural prices) received more attention after the Financial Crisis of 2007-08. The majority of papers claims that there is a clear direction of volatility transmission (from oil to agricultural commodities) and this relationship became stronger recently (mainly after 2006). In other words, agricultural and oil markets became more integrated (DU; CINDY; HAYES, 2011; NAZLIOGLU; ERDEM; SOYTAS, 2013; SERRA, 2011; JI; FAN, 2012) and such integration with a market with higher volatility increased volatility in the agricultural prices.

Regarding biofuels effect on agricultural prices, International Monetary Fund estimated that 70% of marginal increase in corn prices and 40% of soybean prices were caused by demand biofuels expansion (CIAIAN et al., 2011, p.327). OECD-FAO (2013) considered biofuels the main reason for food inflation in 2010s.

On the other hand, some authors say that biofuels can be responsible only for marginal effects on prices, but not for the total effects (AJANOVIC, 2011). Since only 1% of world's agricultural land is used for biofuels production, they would not have enough power to shift demand. Both assumptions are feasible, but literature widely agrees that biofuels have an effect, at least marginal, in rising agricultural commodities prices. Because of supply inelasticity, marginal effects in demand can be magnified, causing large effects in prices.

Even if competition is only marginal, biofuels compete with food for land, and this competition does not depend if production is based on food or non-food crops. In Brazil, for example, 55% of sugarcane production was allocated to ethanol production, and in the USA this proportion was around 40% of corn production, both considering the harvest for 2010-2011 (SERRA; ZILBERMAN, 2013, p. 141). Considering the world production, the proportion used for ethanol production falls to 15% of corn and 18% of sugarcane (DAYNARD; DAYNARD, 2011).

In Figure 5 it is possible to see a clear positive correlation among biofuels production and commodities prices. However, we cannot say from this correlation that biofuels represents a true and/or only determinant in the commodity prices. There are many correlated effects with expansion of biofuels production. The increases on oil price volatility and agricultural prices volatility are positively correlated with biofuels production. Hence, when empirical estimations consider only biofuels, omitting other effects positively correlated, they are likely overestimating the biofuels effects. According to Oladosu & Msangi (2013, p.54), recent papers are actually revising biofuels effects, reducing the role of biofuels on agricultural commodities inflation.

Also in Figure 5, it is possible to see that all three series (Oil index, EAC and NAC) are above their historical averages (considering our sample). Series are normalized, and values above reference line are indicating prices above period-average. Biofuels production seems to have successive breaks because data are on annual basis, while other series are based on monthly data.

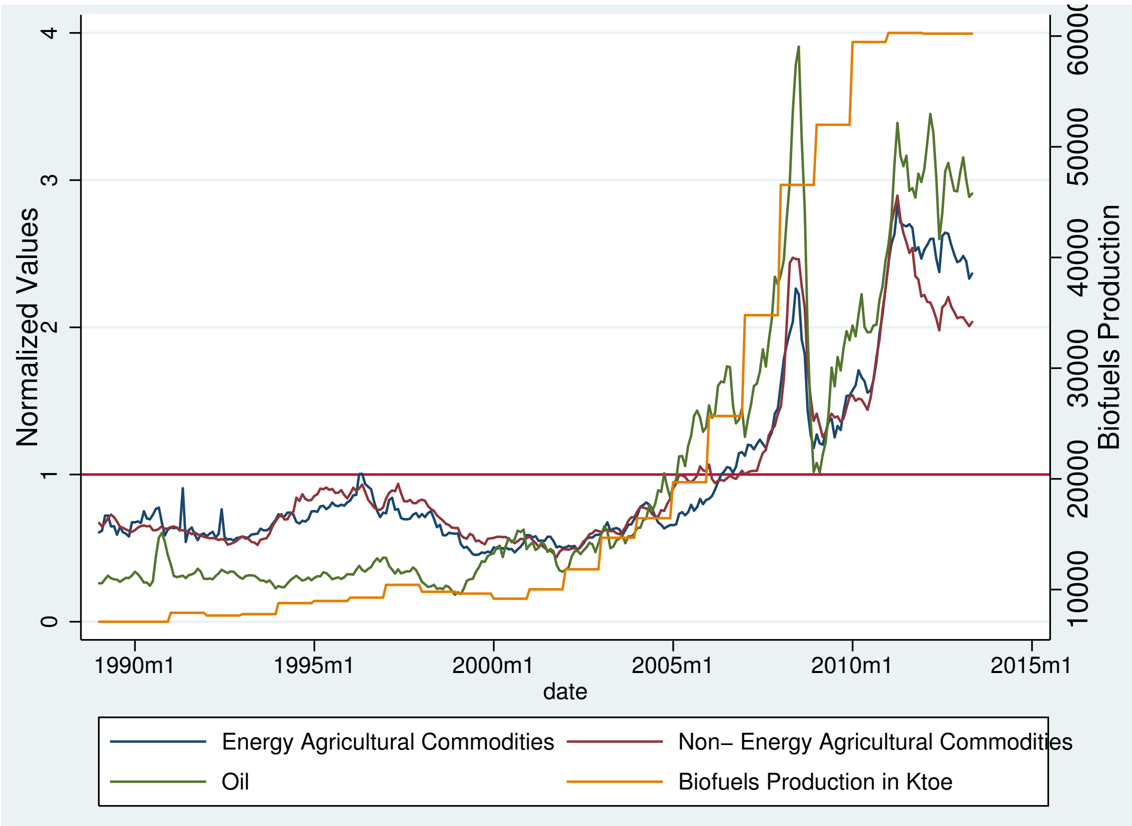

Figure 5 – Oil Prices, Biofuels Production, Energy and Non-Energy Commodities Prices

Source: Authors with prices from IPEADATA and biofuel production from BP(2013). Notes: a) Y=1 is a reference line; b) Biofuels production is on annual basis; c) Values are normalized by their own averages, so, points above one are points above their historical average.

Agricultural markets have expected responses: high prices indicate increasing supply in the next periods and low prices indicate a decreasing supply (OECD-FAO, 2013, p.13). In this context, only high prices cannot drive to long run shortage, because of supply adjustment. But as Mitchell (2008) suggests, high prices associated to high volatility can increase market uncertainty and generate food insecurity due to the less than optimal investment volume due to high uncertain scenario.

There is need to be cautious about the claim of a tradeoff between biofuels and food insecurity, as suggested by OECD-FAO (2013) and Serra & Zilberman (2013). Since biofuels production occurs in food-secure regions (US, Brazil and

Europe), for biofuels create food insecurity there would be necessary to have the assumption that saved crops in food-secure regions can be hunger-minimizer in food-insecure regions. But this is not feasible, since geographic distances prohibit this trade. Then, the alternative that biofuels are causing hunger could be through price transmission. However, regions that are suffering by hunger are so economically isolated that this transmission is far to be an issue (OECD-FAO, 2013, p.55).

Literature about price transmission in agricultural markets is large and an extensive review can be found in Serra & Zilberman (2013). These authors also bring a review on empirical estimations of commodities prices volatility. Vector error-correction models (VECM) of Engle and Granger (1987) changed the way to study price transmission, allowing for short and long run interactions, and giving a better statistical treatment for non-stationary series, features that made it the workhorse of price transmission empirical studies.

Similar changes occurred with Autoregressive Conditional Heterocedastic (Arch) models, also proposed by Engle (1982) in his study about volatility. Seminal Arch models were not fully able to model volatility transmission because they modelled volatilities using just own past volatilities (there is no transmission of volatility among variables, just the past of the own variable matters to explain its volatility). More recent developments, such as Garch-in-mean and Mgarch models, allowed better specifications of volatility transmission.

About cross volatility in agricultural markets, Busse, Brümmer & Ihle (2010) studied volatilities in agricultural commodities using a Mgarch model in returns of rapeseed and crude oil. Using daily dataset (1999 to 2009) they found an increasing correlation between rapeseed and oil prices, indicating a high integration between these two markets and closer responses on rapeseed market to oil market fluctuations.

Serra (2011) studied transmission among oil, ethanol and sugar prices on weekly basis (2000 to 2008) and found that increases in oil prices contributed to ethanol markets to achieve higher equilibrium prices, while they caused just short run instability in sugar prices, driving some volatility. They used a Seo's method that includes an estimation using VECM in mean equation and Mgarch for volatilities.

Nazlioglu, Erdem & Soytas (2013) investigated price volatility spillovers between oil and selected agricultural commodities (wheat, corn, soybeans and sugar) on daily basis (1986 to 2011). Regarding the tools, they used univariate Garch and causality tests. Their results indicated that food crisis increased the link between oil price and agricultural markets. Before the crisis, there was no price transmission from oil to agricultural markets, but after the food crisis there were some transmission in corn, wheat and soybeans markets. Sugar market seems to not respond to oil shocks. The break for the food crisis was 2005.

2.3 ECONOMETRIC APPROACH

In conventional models, variance of disturbance term is assumed to be constant. But it is not true for many time series, especially when there is some break or structural change that likely changed volatility parameters (ENDERS, 2008, p.111). In price series, for example, observations with high volatility are commonly followed by high volatility observations, and this clustered behavior is also found in low volatility periods (FRANSES, 1995, p.24). The empirical verification of this (volatility is not a constant, but we have a function to describe it) implies that the majority of econometric models cannot be applied because of homoscedasticity assumption. The natural next step after verified heteroskedasticy is the use of models that allow conditional heteroskedasticy[7]. In a formal way, considering a common first moment regression:

$$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t \tag{2.1}$$

To assure that OLS to be a BLUE estimator, $Var(\varepsilon_t \mid X_t)$ needs to be constant. One of the first models that tried to relax this assumption was the

[7] Financial crisis in 2007-08 is a clear source of increasing volatility in commodities prices and it is pointed as one of reasons for increasing the use of time-varying volatility models (AIELLI; CAPORIN, 2014).

Autoregressive Conditional-Heteroscedasticity (Arch) model from Engle (1982) that modelled the second moment of regression as an Arch (q):

$$E(\varepsilon_t^2 \mid \varepsilon_{t-1}) = H_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{2.2}$$

In order to allow just positive conditional variances, α_0 and α_1 need to be both larger than zero. Note that the expected variance is an equally weighted average of squared residuals from the past, and these weights will be estimated as parameters of the model, choosing the best weights to forecast the variance (ENGLE, 2002, p. 159). The generalization of this model is a Generalized Autoregressive Conditional-Heteroscedasticity (Garch (p, q)) that also includes lagged H_t:

$$H_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i H_{t-i} \tag{2.3}$$

Then, to find the long run variance in Equation 2.3, the variance of steady state, we need to calculate $H = \alpha_0/(1 - \alpha_1 - \beta_1)$. If $\alpha_1 + \beta_1 = 1$, the long run variance cannot be estimated and it is necessary to use an Integrated Garch (Igarch) (MARGARIDO; AZEVEDO; SHIKIDA, 2012; NELSON, 1990).

In the GARCH specification, as proposed by Engle & Bollerslev (1986), all parameters are restricted to be larger than zero. The idea behind Equation 2.3 is that a mix between long run variance (β) and variance in recent periods (α) is a good predictor of the next period variance. The evolution of GARCH models is the generalization of univariate case in direction to a Multivariate Generalized Autoregressive Conditional-Heteroscedasticity (Mgarch). The generalization for the covariance matrix **H** for a Mgarch (1,1) is usually expressed by:

$$vech(H_t) = C + \alpha vech(\varepsilon_{t-1}\varepsilon_{t-1}') + \beta vech(H_{t-1}) \tag{2.4}$$

Where vech is the column-staking operator of the lower portion of a symmetric matrix[8] and α, β, and **C** are matrix coefficients. The first problem to apply

[8] Considering a symmetric matrix A (2x2) $= \begin{pmatrix} a_{11} & a_{11} \\ a_{21} & a_{22} \end{pmatrix}$, as $a_{12} = a_{21}$, the $vechA = \begin{pmatrix} a_{11} \\ a_{12} \\ a_{22} \end{pmatrix}$.

full *vech* in Mgarch models is the fast increasing of the number of parameters. Just with three series the number of coefficients in a full *vech* generates 78 parameters. It caused the need for re-parameterization to estimate Mgarch (SILVENNOINEN; TERÄSVIRTA, 2009, p.2). Another reason to impose restrictions to H_t is to guarantee that it is positive definite. The variance and covariance matrix for a unique component vech-diag in a bivariate case (commodities 1 and 2) is expressed by:

$$\begin{pmatrix} H_t^{11} \\ H_t^{12} \\ H_t^{22} \end{pmatrix} = \begin{pmatrix} C_0^{11} \\ C_0^{12} \\ C_0^{22} \end{pmatrix} + \begin{pmatrix} \alpha_1^{11} & 0 & 0 \\ 0 & \alpha_1^{21} & 0 \\ 0 & 0 & \alpha_1^{22} \end{pmatrix} \cdot \begin{pmatrix} \epsilon_{t-1}^1 . \epsilon_{t-1}^1 \\ \epsilon_{t-1}^1 . \epsilon_{t-1}^2 \\ \epsilon_{t-1}^2 . \epsilon_{t-1}^2 \end{pmatrix} + \begin{pmatrix} \beta_1^{11} & 0 & 0 \\ 0 & \beta_1^{21} & 0 \\ 0 & 0 & \beta_1^{22} \end{pmatrix} \cdot \begin{pmatrix} H_{t-1}^{11} \\ H_{t-1}^{12} \\ H_{t-1}^{22} \end{pmatrix} \tag{2.5}$$

Note that Equation 2.5 does not allow for cross-volatility, since all elements out-off principal diagonal are equal zero (WANG; WU, 2012, p.2169). So, the volatility of commodity 1 is determined just for its own past volatility and its own cross-product of error term. Remember that our question is *"how oil drives volatility to energy and non-energy agricultural commodities"*, so we need to compute the volatilities spillovers. Hence, we need to use a model to allow for a richer dynamic in volatility as BEKK[9], CCC or DCC models[10]. Among the possible models we will use here are the Constant Conditional Correlation (CCC) and the Dynamic Conditional Correlation (DCC).

The CCC models are specified in a hierarchical way, and at first a GARCH is chosen for conditional variance (for each one, if there are 10 series, it is possible to have one process for each of the series). Second, with the results of conditional variance, it is specified the conditional correlation matrix (BAUWENS; LAURENT; ROMBOUTS, 2006, p.88). It is important to not consider conditional covariance as conditional correlation. In CCC, conditional correlation is constant, but the conditional covariance "move just enough to keep correlations constant" (ENGLE,

[9] BEKK is reference to the authors: Baba, Engle, Kraft and Kroner. For more information see Engle & Kroner (1995).

[10] For more information see Bauwens, Laurent & Rombouts (2006), Silvennoinen & Teräsvirta (2009), Engle (1982) and Engle (2002).

2009, p.37). In CCC model it is expressed by:

$$H_t = D_t R D_t = \rho_{it}\sqrt{h_{iit}h_{jjt}} \tag{2.6}$$

Where,

$$D_t = diag(\sqrt{h_{11t}}...\sqrt{h_{nnt}}) \tag{2.7}$$

In Equation 2.6, R is a positive definite matrix with constant conditional correlations ρ_{it} where the principal diagonal has all numbers equal to one. The CCC models were proposed by Bollerslev (1990) and, from his model, Engle (2002) proposed a DCC model. Note that in DCC model R matrix is time-dependent:

$$R_t = diag(q_{11t}^{\frac{-1}{2}} \cdots q_{nnt}^{\frac{-1}{2}})Q_t diag(q_{11t}^{\frac{-1}{2}} \cdots q_{nnt}^{\frac{-1}{2}}) \tag{2.8}$$

Where,

$$Q_t = (1 - A - B)\overline{Q} + A\varepsilon_{t-1}\varepsilon'_{t-1} + BQ_{t-1} \tag{2.9}$$

And, because R is now time-dependent, Equation 2.6 becomes:

$$H_t = h_{ijt} = D_t R_t D_t = \rho_{ijt}\sqrt{h_{iit}h_{jjt}} \tag{2.10}$$

Then, the diagonal elements in Equation 2.9 are modeled as univariate GARCH, and the elements off-diagonal are nonlinear functions of diagonal terms. In DCC the matrix D_t will be the same as reported in Equation 2.7, with all elements off-diagonal being equal zero. In a study with 3 variables (as ours) D_t will be:

$$D_t = diag(h_{1t}^{\frac{1}{2}}, h_{2t}^{\frac{1}{2}}, h_{3t}^{\frac{1}{2}}) = \begin{pmatrix} h_{1t}^{\frac{1}{2}} & 0 & 0 \\ 0 & h_{2t}^{\frac{1}{2}} & 0 \\ 0 & 0 & h_{3t}^{\frac{1}{2}} \end{pmatrix} \tag{2.11}$$

Where each conditional covariance can have a constant, an Arch term and a Garch term, as in Equation 2.3.

The parameters A and B (Equation 2.9) need to be positive and respect the restriction $A+B<1$. $\overline{Q}$ is the matrix with unconditional variance of the series. Even using one of the most flexible models to measure volatility, there are still restrictions. The most obvious restriction comes from the fact that A and B are scalars numbers and not matrix, implying that all series have the same dynamics[11]. The matrix Q_t could be seen as an ARMA process capturing the short run dynamics (Hernandez and Robles, 2013, p. 8) and $\overline{Q}$ is the long run forecast of variance (Enders, 2004, p. 112).

If $A=B=0$, the model used should be the CCC model. In other words, if there is no evidence that correlations are time-varying, a CCC model is the most indicated. In the case of restriction $A+B<1$, it is necessary to ensure that the model will be stationary. If $A+B=1$, the model is still stationary, but just "weakly stationary" (ENGLE, 2002). With $A+B=1$ we have an Integrated Mgarch. So, there are three main possibilities to quasi-correlations: a mean-reverting process, an integrated process and an asymmetric process (Engle, 2009). In this study we will explore the mean-reverting possibility. Note that, the first step, estimating the conditional variance, allows for different processes and here we consider the possibility of this step to be integrated. But, for quasi-correlations we will explore just the mean-reverting process.

2.4 DATA AND UNIT ROOT TESTS

The economic series used in this paper are the spot prices on monthly basis for oil, sugar, cotton, soybean, coffee, corn, sunflower, rice and wheat. The series can be easily found on different databases such as Ipeadata, Food and Agriculture Organization (FAO) and Chicago Board of Trade (CBOT). Prices to international trade are in US dollars, and to convert spot prices to real prices we used the Con-

[11] It is possible to give particular dynamics to each of the series attributing to them scalars α and β in the matrix of parameters, but again, there is a tradeoff between number of parameters and model flexibility.

sumer Price Index for All Urban Consumers from Bureau of Labor Statistics. The series are from January/1989 to May/2013 (293 observations).

We defined **energy agricultural commodities (EAC)** as those commodities that, in addition to have a supply link with oil market through the use of fertilizers, they have also a demand link by biofuels production. Hence, sugar, corn and soybean are used to create the Energy Agricultural Commodities Index (EAC). EAC index is the result of geometric average of sugar, corn and soybean indexes. The **non-energy agricultural commodities (NAC)** were defined as agricultural commodities that have just the first link (by fertilizers) with the oil market. Therefore, the other commodities that are used to construct the NAC Index are: cotton, coffee, sunflower, rice and wheat. Table 7 illustrates the summary statistics for our database.

The variables need to be stationary to be included in the MGARCH models.

Table 7 – Summary Statistics for the variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Real Prices					
Oil	293	41.88	31.58	10.41	132.55
Coffee	293	107.48	49.00	37.67	270.30
Cotton	293	73.00	25.65	37.22	229.67
Corn	293	139.49	63.44	75.06	332.95
Rice	293	338.63	148.85	162.10	1015.21
Sugar	293	12.95	5.19	5.68	27.61
Sunflower	293	803.96	391.89	332.55	2300.19
Wheat	293	183.62	70.05	102.16	439.72
Soybean	293	625.05	264.73	321.40	1414.40
Price Index					
EAC Index	293	0.42	0.27	0.19	1.20
NAC Index	293	0.49	0.28	0.21	1.39
Oil Index	293	0.34	0.33	0.06	1.34
Return Index					
Oil Return	293	0.00	0.09	-0.37	0.48
EAC Return	292	0.00	0.06	-0.37	0.24
NAC Return	292	0.00	0.04	-0.22	0.22

Source: Author, with data from Ipeadata, FAO and CBOT.

Using just first generation unit root tests, Augmented Dickey-Fuller (ADF) and Philips Perron (PP) tests, in presence of structural changes, there is a "potential confusion of structural breaks in the series as evidence of nonstationarity" (Baum, 2001, p.9). In other words, ADF and PP are biased in direction to wrongly accept the null of existence of unit root in presence of non-linear trends. Since our sample is from January/1989 to May/2013, we need to test that for the possibility of structural breaks.

Beyond confusion (structural breaks-unit roots) ADF and PP also have a binary restricted option for I(d): I(1) or I(0). But, as pointed by Banerjee & Urga (2005), the empirical literature of time series has been walking in the direction of does not simply to test an I(1) null against an I(0) alternative hypothesis, but in direction to allow fractionated values for I(d). In this sense, unit roots and stationary processes are just special cases of fractional integration where 'd' is respectively 1 and 0, but a range of other results are possible.

Therefore, a lot of integrated series are being revised in direction on having a long memory process ($d>0.5$) instead of I(1) process (BANERJEE; URGA, 2005). Other reason to suppose that series are not I(1) is the persistency of shocks, if series are a true I(1), shock's effects would never die. Rappoport & Reichlin (1989) and (PERRON, 1989) argue that most part of shocks in economy is transitory and not permanent, but, at the same time, most of series are diagnosed as I(1) process.

New findings about integration order in time series require for a revision in procedures. Previously, cycles were understood as the sum of a secular trend (linear) and a cyclical component (stationary), and it spreads and justifies the use of filters and differentiated series. Nelson & Plosser (1982) were the first to consider that "stochastic nature of the trend should be considered" (BANERJEE; URGA, 2005, p.3). Hence, procedures were revised in sense that mechanical use of ADF and PP (test the series → reject the null of stationarity → use series filtered or differentiated) are not indicated. This approach frequently confuses uncounted breaks and long memory processes with unit root process.

Granger & Hyung (2004)[12] indicate a procedure that consists of three basic steps: i) estimation of 'd' by GPH test; ii) investigation about breaks; iii) considering the breaks, 'd' is estimated again. This procedure attempts to distinguish between unit roots, long memories and breaks. Only when $d = 1$, after accounted for breaks, that we can be sure that a time series is I(1).

We will use QLR test proposed by Quandt (1960) and revised by Andrews (1993) to test the possibility of breaks [13]. After 1993 there was another correction of parameters values in Andrews (2003), but values are very similar, with exception for eight degrees of freedom. Note also that values in Table 1 in Andrews (1993) still need to be divided by $q = 5$ (in our case, four lags and the constant used in tests resulted in q=5). Therefore we use the critical value of 3.66 and not 18.35 to investigate breaks presence. This is a modified version of Chow test for unknown breaks. Here it is not supposed a specific date for break, and the test is done recursively. The QLR test results are plotted in Figure 6, where points above the reference line indicate the presence of breaks.

QLR tests showed a similar pattern considering the Financial Crisis of 2007-08 as a break in three series. Trim parameter of 0.15 means that 15% of sample in each extreme was discarded, which is the default procedure because of the test is biased by initial and final values, and the bias goes in the direction to consider breaks that actually do not exist. For this reason, we did not consider the EAC and NAC first breaks (around 1992:m8) as a true break. NAC was the only one among the three series that we will consider having two breaks: first in 2007:m1 and the second around 2002:m1. QLR statistic does not qualify the type of break, so, we cannot decide if the break is in the intercept, in the trend or in both. Finally, a filter is used in the series considering the possibility of break in intercept, in trend and in both possibilities (intercept and trend).

After these diagnostic tests about the presence of breaks, we test a modified

[12] An interesting empirical use of this method for the Brazilian economy can be found in Silva & Vieira (2013).

[13] More information about critical values are found in Andrews (1993, p.840,Table 1).

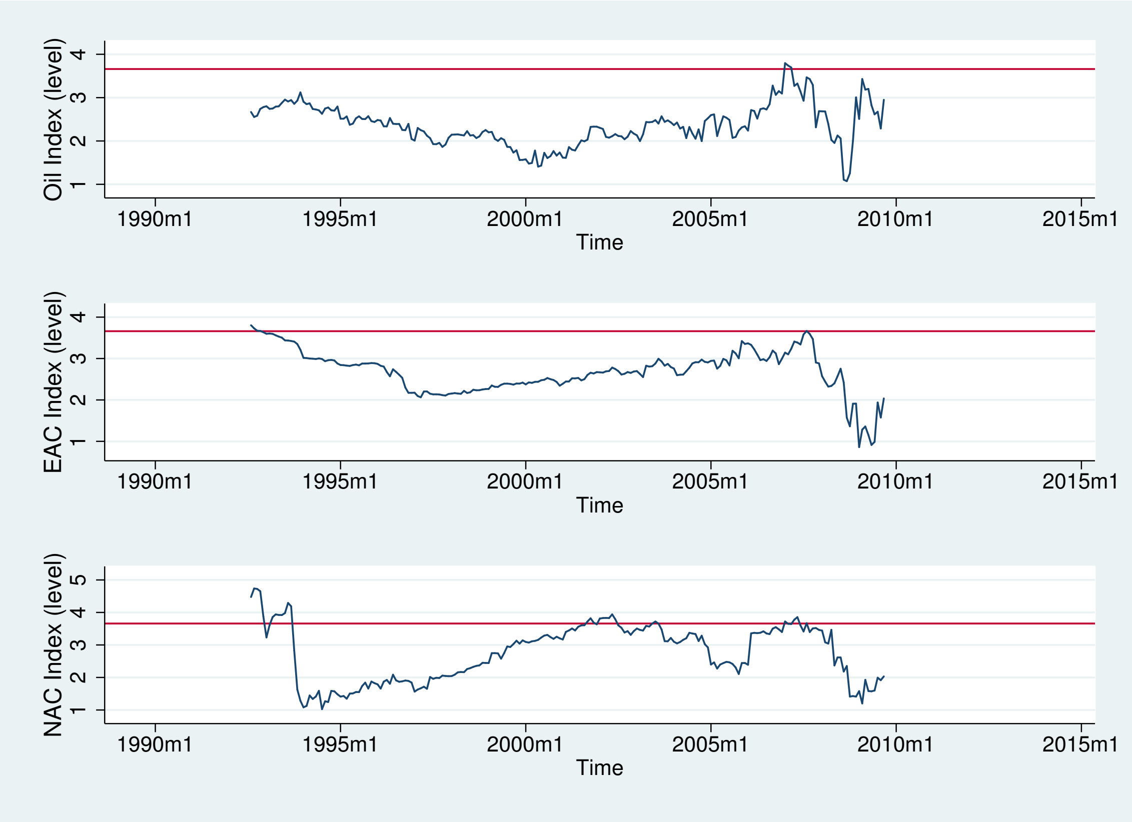

Figure 6 – Testing for Breaks - Prices - QLR statistic

Source: Authors. Notes: a) Y=3.66 is a reference line for 5% critical value; b) Trim parameter = 0.15 (15% of each side of distribution is dropped).

version of Geweke & Porter-Hudak (1983) or (GPH test) proposed by Phillips (1999), called here as Phillips' modified LPR[14]. Phillips (1999) argues that original GPH is inconsistent for $d > 1$. We test that in the original series (Y_t) and in filtered series $(Y_t - Z_t)$, where Z_t is the vector of breaks. Considering an intercept break, Z_t is 1 if $t > t_b$, and 0 otherwise. Considering a trend break, Z_t have values $t - t_b$ if $t > t_b$, and 0 otherwise. For this test we have two important null hypothesis ($d = 0$ and $d = 1$), Table 8 brings these results.

Table 8 indicates that data generating process of our indexes are not explosive, especially when breaks are considered. In two indexes (Oil and NAC) we cannot reject the null of $d = 0$ and strongly rejected the null of $d = 1$. In other

[14] Abbreviation for Log Periodogram Estimator.

Table 8 – Phillips' modified LPR test for fractional integration (d)

	Yt	Yt-Intercept	Yt-Trend	Yt-Both
Oil Index (Level)	0.3554	-0.0214	0.6239	0.3169
Std. Err.	0.1675	0.1777	0.0672	0.0704
Ho(d=0) (t)	2.1220**	-0.1205	9.288***	4.5011***
Ho (d=1) (t)	-4.1448***	-6.5672***	-2.4182**	-4.3918***
EAC Index (Level)	0.7647	0.4752	0.4528	0.3232
Std. Err.	0.1803	0.1016	0.1460	0.1293
Ho(d=0) (t)	4.2419***	4.6789***	3.1014***	2.5006**
Ho (d=1) (t)	-1.5131	-3.3744***	-3.5182***	-4.3513***
NAC Index (Level)	0.5184	0.0377	0.2583	0.0339
Std. Err.	0.2536	0.1967	0.2208	0.2759
Ho(d=0) (t)	2.0443*	0.1919	1.1697	0.1231
Ho (d=1) (t)	-3.0959***	-6.1868***	-4.7685***	-6.2111***

Source: Data from Ipeadata, FAO and CBOT. Author's calculations following procedure proposed by Granger and Hyuong (2004). Notes: a) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. b) Tests for breaks done using QLR statistics, so for all series we used a dummy in 2007:m1 and for NAC series we used an additional dummy in 2002:m1.c) Intercept is a "classic dummy" and trend dummy is an additive dummy, trying to capture a more gradual break.

words, we are far from a unit root process ($d = 1$), and it is possible that processes are stationarity, especially when breaks are considered.

In the returns series we also need to test the possibility of breaks for a better specification of mean equation in Mgarch models. In this case there is no issue about confusing the presence of breaks and unit root, since returns are recognized as being stationary processes. Therefore, we just report the QLR test investigating breaks in returns series (Figure 7).

The series of returns followed the same pattern seen for the series of prices, with a break around the Financial Crisis 2007-08. The more relevant spike detected was around 2007:m1 for prices, and for returns the main spikes were around 2008:m1. Hence, the break for the returns due to Financial Crisis will be 2008:m1 and not 2007:m1. NAC returns also showed two breaks as NAC level prices.

Mgarch models are indicated when there is evidence of conditional hetero-cedastic effects in residuals of mean regressions. Considering that a simple AR(2)

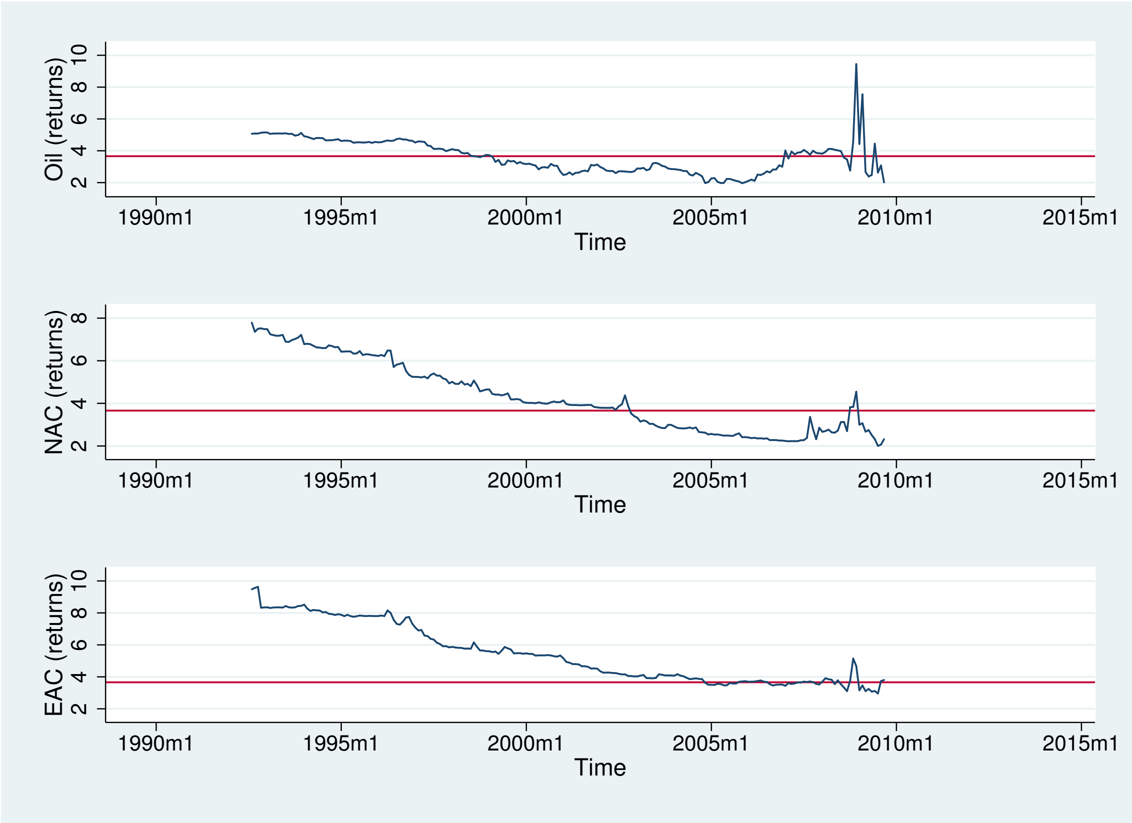

Figure 7 – Testing for Breaks - QLR Statistic - Returns

Source: Authors. Notes: a) Y = 3.66 is a reference line for 5% critical value; b) Trim parameter = 0.15 (15% of each side of distribution is dropped).

process is a good specification for series (means) of prices, I plotted squared residuals and it brings the possibility of cluster volatility. We also estimated the mean equation of returns using just a constant term. Plotting these squared residuals also the possibility of cluster volatility hypothesis in returns series appeared.

A visual inspection of squared residuals should not be a substitute for a formal test (Enders, 2004, p. 111). A test widely used in the presence of Arch effects was proposed by Engle (1982). In order to do the test it requires getting the squared residuals of the mean equation and regressing them against a constant and their lagged values. If the coefficients of lagged values are different from zero (following a chi-distribution), there are Arch effects. Tests' results are in Table 9.

Table 9 – Lagrange Multiplier Test for Arch effects (Ho: no Arch effects)

Series	Lags (p)	Chi2	Prob
EAC Index (Return)	0	34.56	0.00
EAC Index (Level)	2	49.57	0.00
NAC Index (Return)	0	41.56	0.00
NAC Index (Level)	2	50.39	0.00
Oil Index (Return)	0	45.09	0.00
Oil Index (Level)	2	117.51	0.00

Source: Author.
Notes: a) LM Test proposed by Engle (1982); b) I tested all these series considering structural breaks and it was concluded that, even with breaks, Arch effects remained in the residuals; c) Test was repeated with several lags providing similar results.

Formal tests confirm the visual inspection showing strong evidence of cluster volatility, indicating the need for conditional heteroscedasticity specification to model volatilities. In all series tested the null hypothesis of no Arch effects was rejected.

2.5 RESULTS

We proposed an AR(2) process for mean equations and ARMA(1,1) process for volatility equations, for both price models, CCC and DCC, using both Arch and Garch terms. The choice of AR(2) was based on partial autocorrelation functions (not reported here). Following QLR results, relevant breaks were included in the mean and variance equations.

For the series of returns, the mean equations were modelled by a constant plus breaks. There is no reason to believe that an AR(p) is a good predictor for returns because of the efficient market hypothesis[15]. The volatility equations for returns have the same specification used for the price equations, that is, a Garch (1,

[15] Efficient market hypothesis (EMH) says that price market reflects the public available information. Hence, there is no space for a consistent AR(p) process to describe returns.

1).

For a better visualization this section is divided into prices results and returns results. This follows a discussion about some results implications, where we try to compare our results with the empirical literature about commodities prices.

2.5.1 Prices

It was expected that oil index would transfer volatility to commodity prices. In our model it is represented by positive cross-volatility for both agricultural commodities indexes prices (NAC and EAC)(Q. Corr. in Table 10). More than just positive signs, we also expected that cross-volatility for EAC has larger coefficients than NAC ones, indicating that markets with larger links (energy agricultural commodities - EAC) will have larger volatility transmissions.

Mean equations need to respect stability conditions of AR(p) process, the sum of lagged variables should not exceed one to guarantee that process is mean reverting. This condition was guaranteed for all three series.

In the Oil mean equation, the sum of AR(p) parameters is around 0.96, indicating high persistence of level prices. Intercept dummy for 2007 is highly significant for mean and for variance equation, indicating that 2007 has a positive jump in price and in volatility.

The estimated parameters for EAC and NAC mean equations had also a high persistence. The positive and significant intercept dummies indicate that dummies were times of increases in prices.

In the case of long run volatilities, as expected, oil showed higher volatilities than the other two indexes (NAC and EAC). The calculations of the long run variances in the first period (before the first break) showed results around 50 (oil), 27 (NAC) and 7 (EAC)[16]. Positive and significant breaks in volatility are indication that

[16] Long run variance is calculated by $H = const/(1 - \alpha - \beta)$. So, for oil's long run volatility before 2002 we solve $H = 2.986/(1 - 0.536 - 0.404) = 49.76$. Note that intercept dummies are added up to the constant in the calculations for the following periods.

long run volatility changed over time. For oil, for example, the long run volatility was 50 until 2002:m1, approximately 84 (70%more if compared with first period) between 2002:m1 and 2007:m1, and 102 from 2007:m1 until the end of the sample (106% more when we compare with first period).

In the volatility equation, the moving average term (α) indicates that the last period volatility impact (once we use just one lag in the Arch term) and that the autoregressive term (β) indicates the persistence or the role of long run variance in variance forecast. The share between Arch and Garch are also the same in all volatility series; the weight between long run and last period is almost the same, but the magnitude of persistence ($\alpha + \beta$) showed large persistence in Oil and NAC volatility (around 0.9), and little persistence in EAC series (around 0.43).

For the first estimates (without taking into account structural breaks – not reported here) both models, CCC and DCC, for all three series, suggested an Igarch process ($\alpha + \beta = 1$), where shocks in volatility are not dissipated. Franses (1995) and Lamoureux & Lastrapes (1990) highlight the possibility of overstated variances if structural shifts are not taken into account in the model, causing the wrong impression that shocks are permanent. Recently, Hillebrand (2005) treated the same problem and says that omitted variables in the variance equation makes Garch models strongly biased in the direction that parameters sum to one (Igarch). After considering breaks in both equations, the process became mean reverting[17].

According to the estimated quasi-correlations, there is some evidence that oil prices transfer more volatility to energy agricultural commodities. In both models (CCC and DCC), the parameters of quasi correlations are larger for EAC than for NAC. In a general sense we can say that oil increases both volatilities for NAC and EAC, and this relation is statistically significant. There is a positive volatility transmission between NAC and EAC (Q. Corr (EAC, NAC)) and this transmission is larger than the other two relationships (Quasi Correlations between EAC and Oil and

[17] In an ARMA (p,q) process, to ensure that variable has a mean-reverting behavior the condition $(p + q) < 1$ needs to hold. The equivalent condition for volatility equation is that $(\alpha + \beta) < 1$. If it is not valid, it would lead to an explosive data generating process.

between NAC and Oil), which is expected, since there should be more transmission within agricultural markets than from oil market to agricultural markets.

Lambdas 1 and 2 in Table 10 are the adjustment parameters of conditional covariances in DCC model. This is also an ARMA(p,q) process where lambda 1 is lagged values (q) and lambda 2 represents autoregressive term (p). Hence, a larger lambda 2 is indicating that past values have more importance than lagged residuals innovation (BAUM, 2006). The fact that these values are statistically different than zero can be evidence that conditional covariances are time-varying, which indicates to the use of a DCC instead a CCC model. We have used just one proportion between lagged residuals and residual innovations and three quasi-correlations. Summing up, the same process is imposed for all three quasi-correlations, which is clearly one of the limitations of the model (ENGLE, 2002).

These quasi-correlations reported in Table 10 are the mean of the period, so it is impossible to see the behavior of parameters across time. In order to check this we plotted conditional correlation between pairwise of series (8)[18]. The results are indicating that these series are moving in the same direction and, more than this, the degree of correlation increased in recent periods, mainly after the Financial Crisis 2007-08. The conditional variance for each index EAC and NAC also increased, as expected (not reported here).

2.5.2 Returns

For the series of returns (P_t/P_{t-1}) we did not expect a good fit for the first moment equations because of hypothesis that markets are efficient. It is usual in the literature to model series of returns as a random walk process, using just a constant in the mean equation, which is the specification also adopted here.

Different than in the price series, Garch term (β) seems not to be a determinant for volatility (all $\beta's$ were not statistically significant), i. e., long run variance

[18] The output from 'predict' in Stata.12 is conditional covariance and not conditional correlation. We calculated correlation using $Corr(X, Y) = Cov(X, Y)/\sigma_x\sigma_y$.

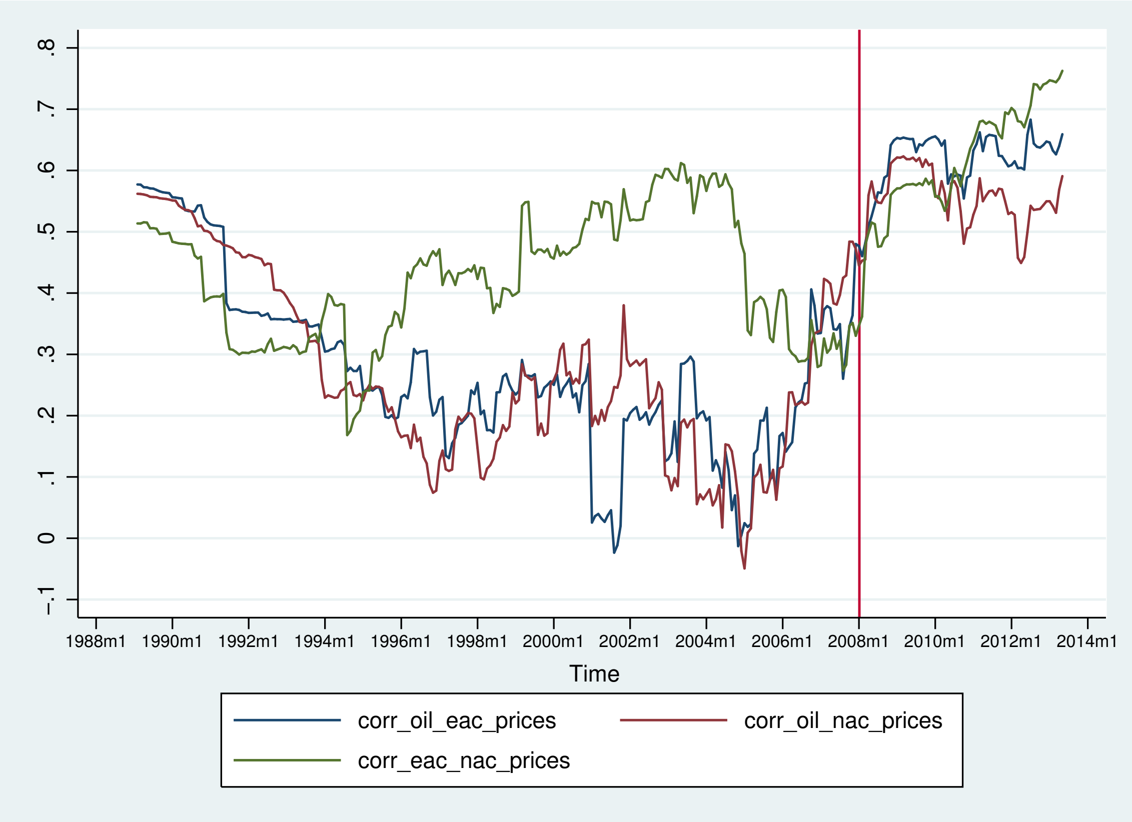

Figure 8 – Conditional Correlation - Prices

Source: Authors using results from DCC model. Note: a) X = 2008m1 is a reference line for Financial Crisis.

did not play a role in the explanation, only (α), the volatility in the previous period, seems to be relevant for returns' variance. Then, persistence of volatility in returns will be given just by the Arch term (α). Into returns results, oil is still accounting for the largest persistence (0.36), but it is much less than the persistence found in the price series. Oil also had the largest long run variance in returns (8.13).

Dummies in volatilities were not significant (we tested also with just one of the two, but the results were similar), the only exception was the intercept dummy for 2008 (DI2008), it was relevant and with the expected sign (positive) for NAC returns, representing a positive impact on volatility (Table 11).

Regarding cross volatility (quasi-correlations parameters), their signs were positive between Oil and EAC in both models. Hence, increases in volatility of Oil likely would be followed by positive spillovers in EAC. In the CCC estimations, these quasi-correlations' parameters were statistically significant, but the opposite occurred in the DCC model.

Differently from the price series, the series of returns have not all series moving in the same direction. Quasi-correlations between Oil and NAC in both models (CCC and DCC) are negative. So returns of Oil and NAC are moving in opposite directions. Note that there is no problem in prices and returns had presented different results, since it is entirely possible to have positive correlations in prices and negative correlations in returns for the same variables.

In order to verify if correlations between series are increasing over time, we have the Figure 9 with Corr (Oil, EAC), Corr (Oil, NAC) and Corr (EAC, NAC).

Figure 9 shows the anticipated results obtained from the estimations for

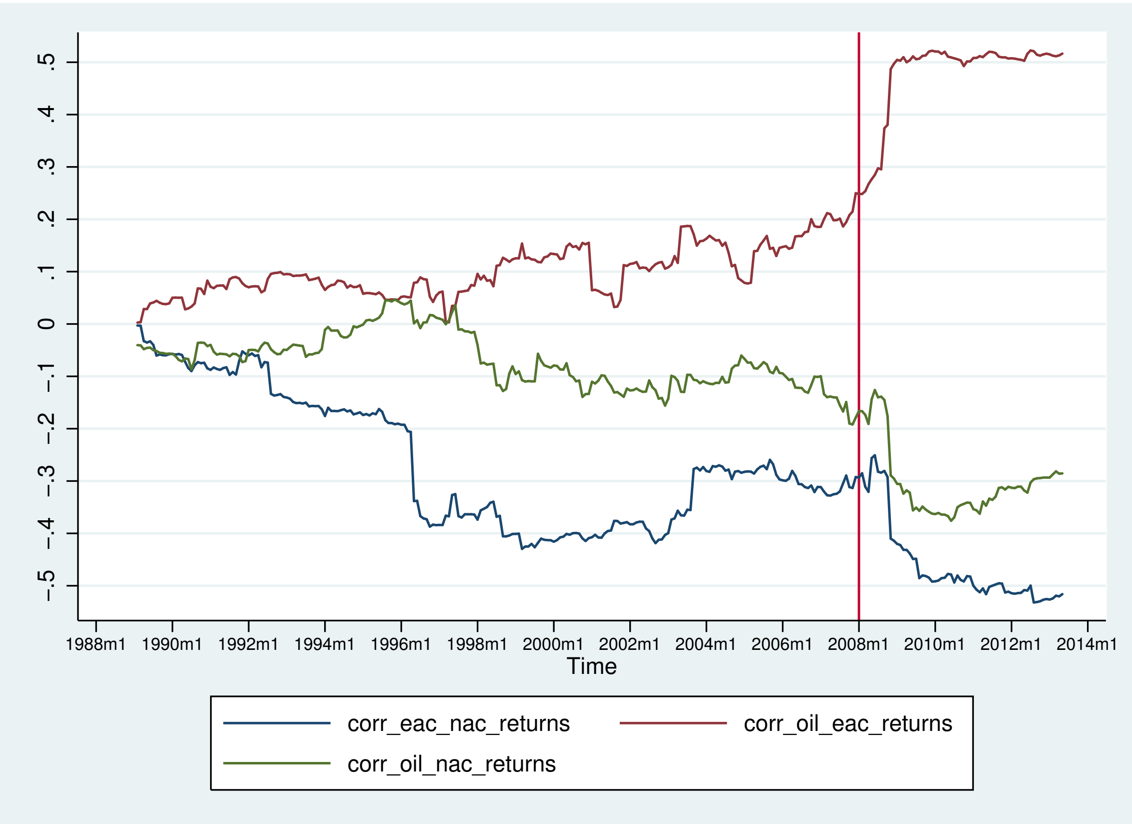

Figure 9 – Conditional Correlation - Returns

Source: Authors with the results from DCC model. Note: X=2008m1 is a reference line for Financial Crisis.

quasi-correlations. The relation between Oil and EAC returns is near to zero, or weakly positive, in the first half of the sample, and it had a strong increase during recent periods. On the other hand, Oil and NAC returns had correlations near zero until 1998, after that correlations were reduced until values near -0.5 in recent periods.

Note that exactly in the peak of the Financial Crisis, last quarter of 2008, we have a break in the series, causing strong increase in Corr (Oil, EAC) and strong reduction in Corr (Oil, NAC).

2.6 DISCUSSION AND IMPLICATIONS

Our results have some implications for traders and policy makers. Agricultural commodities should not be treated as a homogeneous group, especially regarding the transmission volatility and conditional covariance among returns. Considering a portfolio with oil bonds (or bonds correlated with oil), diversification strategies should be revised in direction to consider conditional correlations differences between Energy Agricultural Commodities (EAC) (sugar, soybeans and corn) and Non-Energy Agricultural Commodities (NAC) (coffee, rice, cotton, sunflower and wheat). In this sense, a better diversification strategy can be done with NAC instead of EAC.

These results are in line with the volatility transmission literature regarding the increasing volatility during Financial Crisis and Food Crisis and with increased conditional correlations between oil and agricultural markets. The results about differences in volatility transmission cannot be compared with other studies because we did not find similar research question in the empirical literature.

The literature about agricultural commodity volatility often says that the reasons for its increase are: i) oil spillovers (JI; FAN, 2012; SERRA, 2011); ii) financialization (FLEMING; KIRBY; OSTDIEK, 2005); iii) American monetary policy (ASKARI; KRICHENE, 2008; NAZLIOGLU; ERDEM; SOYTAS, 2013); iv) macroeconomic factors such as increases in demand for commodities from China (GILBERT, 2010); v) biofuels (BABCOCK, 2012; CIAIAN et al., 2011; SERRA, 2011). Note that all factors pointed by the literature are macro factors, so attempts to minimize volatility are very limited[19].

Regarding reasons for large volatility in agricultural markets, note that if the argument of inelasticity in agricultural markets is valid to justify a high price volatility, biofuels should not be a reason for increasing volatility in the long run. They increased demand elasticity in these markets (fuels should be more elastic than food). Then, a natural conclusion is that biofuels should reduce price volatility is correct (supply shocks now can be adjusted also by quantities, not just by prices). It could be true if we are talking about a free market situation, a free market introduction, and it is not the case for biofuels market.

In a free market situation the rise in sugarcane demand by biofuels, for example, would generate increases in prices and quantities to be produced, but there is nothing indicating that this would increase price volatility. The problem is that biofuels are often introduced by mandates (government says that a market share or a fixed quantity is ensured), and this introduction not just shifts demand, but also changes its slope, making demand more price inelastic.

Summing up, biofuels could cause two different price volatility effects in agricultural markets: i) to reduce price volatility because of increase in price elasticity; ii) to raise price volatility because of integration with a more volatile market (oil). But, the nature of insertion (by mandates or fixed mandates) did not allow any kind of reduction in price volatility. This discussion drives us to the question if there is possibility to introduce biofuels without having these collateral effects (increasing in price volatility).

Flex-fuel cars could be an option in a sense of insertion more close to the free market conditions. The use of flex- fuel cars would be given some flexibility to mandates as suggested by Babcock (2012), the blending can change in each fuel

[19] There are also localized issues that likely increase volatility, such as crop shortfalls. For this kind of problem, public countercyclical policies are usually used.

supply, following markets conditions and being a kind of countercyclical mandate (increasing biofuels demand when oil is expensive and decreasing that when oil is cheap).

Serra & Gil (2012) have other two recommendations to mitigate volatility in agricultural markets: i) the use of public stock management or public information about stocks to smooth price transmission; ii) the use of public incentives to estimulate generation biofuels which would to reduce both competition for crops and volatility.

According to Afiff et al. (2013), biofuels policies are in a turning point. Two of major sponsors by global biofuel demand, US and Europe, are revising their policies, and they are concerned with collateral effects as deforestation and global hunger, and also with supply capacity. The vision of policies in direction to give less importance to biofuels probably will reduce market integration, being other quasi experiment scenario and a nice start point for new researches.

2.7 CONCLUSIONS

In this study we tried to answer if there are volatility spillovers from oil market to agricultural commodities, and if there are differences in this transmission by type of agricultural commodities into two groups: i) agricultural commodities that are used in biofuels production (EAC) – corn, sugarcane and soybean; ii) agricultural commodities that are not used in biofuels productions (NAC) – coffee, rice, cotton, sunflower and wheat.

The information about volatility spillovers were in the conditional correlations estimated with Mgarch model parameters. Results showed that prices of the three indexes, Oil, EAC and NAC, move in the same direction. On the other hand, results for returns showed that conditional correlations between Oil and EAC are positive, and negative for Oil and NAC. The graphs of predicted conditional correlations (Figure - 8 in page 70 and Figure - 9 in page 71) showed that correlations became stronger in recent periods with high peaks during Financial Crisis 2007-08. This result highlights that an old strategy of traders, to invest in agricultural commodities bonds trying to diversify their portfolios, could be a mistake. First, because there is high conditional covariance between oil and EAC returns, then this kind of agricultural commodity is not the best option to diversify portfolios composed by oil bonds and other assets high correlated with oil. Second, this covariance becomes higher especially in those periods where diversification strategies are more important, during the crisis. For a better diversification, NAC bonds are likely a better option than EAC ones.

According to the research question addressed in this study, future research agenda can mainly proceed in two ways: i) other statistical approaches to measure volatility and its spillovers; ii) try to find other reasons why agricultural commodity volatility increased, as well some instruments to reduce it.

Our use of DCC had the assumption that volatility has a mean-reverting data generating process, and the behaviour of our lambdas corroborated this assumption, but it is still possible to test other possibilities as asymmetric dynamics or the use of other econometric approaches to measure volatility spillovers, as the test proposed by Hafner & Herwartz (2008). Since the present study used monthly basis data, the re-estimation of the model using daily or weekly data also can be an interesting improvement.

Regarding the reasons on why volatility in agricultural markets is increasing, we tried to start this investigation supposing that biofuels have a role in this explanation. But, research considering other factors are necessary, mainly in a sense of accounting for all factors that are positive correlated all together (macro factors, financialization and American monetary policy, for example).

Most attempts to reduce the price volatility are not feasible because the possible instruments are out of control (oil market prices, China's demand, and others). Alternatively, policy makers could try a different market insertion in biofuels case, which drives less volatility than the actual policies adopted. Policies that allow for a market self-adjustment, such as the use of flex fuel cars instead of mandates, for example.

Table 10 – Results for CCC and DCC using Price series

	CCC		DCC	
Variables	Coef.	Int. Coef.	Coef.	Int. Conf.
Oil				
L.Oil	1.250***	[1.130,1.371]	1.263***	[1.148,1.378]
L2.Oil	-0.299***	[-0.419,-0.180]	-0.314***	[-0.428,-0.199]
DI2007	42.28***	[20.58,63.97]	42.79***	[20.04,65.55]
_cons	5.999***	[2.617,9.380]	6.255***	[2.787,9.722]
ARCH_Oil				
Arch (α)	0.404***	[0.193,0.615]	0.363***	[0.156,0.570]
Garch (β)	0.536***	[0.365,0.707]	0.563***	[0.381,0.746]
DI2002	2.063***	[1.074,3.051]	2.219***	[1.201,3.237]
DI2007	1.117	[-0.123,2.356]	1.707**	[0.604,2.810]
_cons	2.986***	[2.125,3.848]	2.831***	[1.869,3.793]
EAC				
L.EAC	1.019***	[0.876,1.162]	1.037***	[0.911,1.162]
L2.EAC	-0.0492	[-0.189,0.0911]	-0.0670	[-0.191,0.0570]
DI2007	8.056*	[1.750,14.36]	7.299*	[1.315,13.28]
_cons	3.606*	[0.726,6.487]	3.885**	[1.244,6.527]
ARCH_EAC				
Arch (α)	0.212**	[0.0798,0.344]	0.206**	[0.0762,0.336]
Garch (β)	0.277	[-0.0105,0.565]	0.226	[-0.0717,0.524]
DI2007	1.386***	[0.903,1.869]	1.864***	[1.381,2.347]
_cons	3.362***	[2.869,3.855]	3.411***	[2.932,3.891]
NAC				
L.NAC	1.330***	[1.208,1.452]	1.279***	[1.158,1.400]
L2.NAC	-0.359***	[-0.480,-0.237]	-0.311***	[-0.432,-0.189]
DI2007	5.962***	[2.837,9.087]	6.082***	[2.823,9.340]
_cons	2.738***	[1.246,4.230]	3.083***	[1.514,4.651]
ARCH_NAC				
Arch (α)	0.433***	[0.227,0.639]	0.532***	[0.276,0.789]
Garch (β)	0.454***	[0.258,0.650]	0.397***	[0.165,0.630]
DI2007	2.043***	[1.289,2.797]	2.453***	[1.656,3.249]
_cons	1.041**	[0.300,1.783]	1.180**	[0.318,2.042]
Q.corr(Oil, EAC)	0.277***	[0.164,0.390]	0.929	[-1.103,2.961]
Q.corr(Oil, NAC)	0.263***	[0.149,0.377]	0.856	[-1.170,2.882]
Q.corr(NAC, EAC)	0.429***	[0.330,0.527]	1.213	[-0.930,3.357]
Adjustment				
lambda1			0.0435**	[0.0163,0.0707]
lambda2			0.951***	[0.915,0.987]
N	291		291	
AIC	6414.7		6383.4	
BIC	6517.5		6493.6	

Source: Authors. Mean Equation: $Y = AR(2)$; Variance Equation $H_t = w + \alpha.Arch + \beta.Garch + \epsilon$. Notes: a) 95% confidence intervals in brackets; b) * p $<$ 0.05, ** p $<$ 0.01, *** p $<$ 0.001.

Table 11 – Results for CCC and DCC using Returns series

	CCC		DCC	
Variables	Coef.	Int. Conf.	Coef.	Int. Conf.
Oil				
_cons	1.631*	[0.290,2.973]	1.449*	[0.138,2.759]
ARCH_Oil				
Arch (α)	0.390***	[0.185,0.595]	0.384***	[0.180,0.589]
Garch (β)	-0.0498	[-0.211,0.112]	-0.106	[-0.376,0.163]
DI2002	0.106	[-0.398,0.610]	0.201	[-0.306,0.708]
DI2008	-0.601	[-1.231,0.0295]	-0.242	[-0.908,0.423]
_cons	4.801***	[4.446,5.157]	4.823***	[4.417,5.229]
EAC				
_cons	0.00789**	[0.00195,0.0138]	0.00567*	[0.0000461,0.0113]
ARCH_EAC				
Arch (α)	0.211***	[0.0863,0.336]	0.199**	[0.0756,0.323]
Garch (β)	0.248	[-0.0721,0.569]	0.0554	[-0.725,0.835]
DI2002	-0.575*	[-1.059,-0.0905]	-0.473	[-0.958,0.0121]
DI2008	0.0736	[-0.543,0.690]	0.516	[-0.0949,1.127]
_cons	0.00167***	[0.000764,0.00258]	0.00200***	[0.000904,0.00310]
NAC				
_cons	-0.108	[-0.300,0.0842]	-0.0909	[-0.283,0.101]
ARCH_NAC				
Arch (α)	0.167*	[0.00675,0.328]	0.161*	[0.00136,0.321]
Garch (β)	0.330	[-0.000850,0.660]	0.326	[-0.00963,0.663]
DI2002	-0.0127	[-0.529,0.503]	0.0411	[-0.472,0.554]
DI2008	0.903**	[0.321,1.485]	1.081***	[0.505,1.657]
_cons	0.243	[-0.375,0.861]	0.251	[-0.370,0.872]
Q.corr(Oil,EAC)	0.301***	[0.192,0.410]	2.037	[-0.909,4.983]
Q.corr(Oil,NAC)	-0.153**	[-0.266,-0.0394]	-1.266	[-3.393,0.861]
Q.corr(EAC,NAC)	-0.383***	[-0.482,-0.284]	-1.621	[-3.863,0.620]
Adjustment				
lambda1			0.0178	[-0.00123,0.0368]
lambda2			0.976***	[0.966,0.987]
N	292		292	
AIC	2518.8		2484.0	
BIC	2596.0		2568.5	

Source: Authors. Mean Equation: $Y = const$; Variance Equation:$H_t = w + \alpha.Arch + \beta.Garch + \epsilon$. Notes: a) 95% confidence intervals in brackets; b) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3 PRICE ASYMMETRY AND RETAILERS HETEROGENEITY IN BRAZILIAN GAS STATIONS

Abstract

In a competitive market situation a symmetric price transmission is expected, the speed of adjustment of the market should be equal, no matter which direction input prices are going (up or down). Any deviation from this situation is called price asymmetry transmission. Price transmission has direct implications for welfare distribution, positive price asymmetry (when firms react faster to increases in input prices than decrease in inputs), for instance, is related to transfer of welfare surplus from consumers to producers. Stressed the importance of studying price asymmetry, this chapter aims to answer three questions: i) Is there price asymmetry in Brazilian Gasoline Market? ii) Is asymmetry a firm or a market feature? iii) Which variables contribute to the likelihood of gas stations to respond asymmetrically? To answer these we run an AECM for more than 17,000 gas stations. Results indicate that there is heterogeneity across gas stations: 71% of them have no asymmetry, 23% have positive asymmetry and 6% have negative asymmetry. Regarding the importance of variables on the probability to respond asymmetrically: gas stations with higher margins, less rivals nearby and non-white flags have higher probability to have positive asymmetry, reinforcing linkage between positive asymmetry and market power. Results reinforce the link between power market and positive price asymmetry and bring the novelty of relating that also with spatial competition.

Keywords: firms heterogeneity, asymmetric price, gas stations, gasoline.

Resumo

Em um mercado competitivo uma transmissão simétrica de preços é esperada, a velocidade do ajuste aos choques não deve ser diferente para choques positivos nos custos e para choques negativos. Qualquer desvio desse padrão é chamado de assimetria de preços. Transmissão de preços tem impactos diretos na redistribuição dos excedentes do consumidor e do produtor. Por exemplo, quando as firmas reagem mais rápido a aumento dos custos do que à diminuição desses (assimetria positiva) existe uma transferência de excedente dos consumidores para os produtores. Se ocorre o contrário, a velocidade é maior quando os preços dos insumos caem do que quando eles sobem (assimetria negativa), os consumidores estarão em uma melhor situação e os produtores em uma pior situação. Colocado isso, esse capítulo objetiva responder a três perguntas: i) Existe assimetria de preço no mercado brasileiro? Assimetria é uma característica das firmas ou do mercado como um todo? iii) O que aumenta ou diminui a chande de um posto praticar assimetria? Foi usado um AECM para mais de 17 mil postos e os resultados indicam para a existência de heterogeneidade: 71% dos postos não responde assimetricamente, 23% responde positivamente e 6% negativamente. A respeito de quais variáveis mudam as chances de uma firma responder assimetricamente, os postos com maiores margens e com bandeira diferente da branca possuem maior probabilidade de ter assimetria positiva, reforçando o link entre assimetria positiva e poder de mercado. Os postos com menos vizinhos num raio de 0.5 possuem maior chance de praticar assimetria positiva, o que, até onde sabemos, é o primeiro resultado relacionando concorrência espacial e assimetria positiva.

Palavras-chave: heterogeneidade das firmas, assimetria de preços, postos, gasolina.
JEL: C24, D22, L11, R32.

3.1 INTRODUCTION

In a competitive market situation a symmetric price transmission is expected, and the speed of adjustment of the market should be equal, no matter which direction input prices are going (up or down). Any deviation from this situation is called price asymmetry transmission. When input prices increase, firms need to pass on costs to avoid negative profit situation. When they go down, firms reaction is in direction to avoid losses of market share (I am considering that inputs are common for the whole market, so, the other firms also face to a reduction in costs). But, how fast do firms react? Do they react always in the same way? Or the speed of reaction depends on the nature of costs shocks: positive shocks having different speeds than negative shocks? Answering these questions is precisely what we do when studying (a)symmetry transmission price.

The standard pattern (price symmetry) is when firms react fully and with the same speed in both situations: when input prices go up and when they go down. The most common deviation of that is when retailers adjust output prices faster when input price goes up than when it goes down. This situation is called as **positive asymmetry**, or a "rockets and feathers pattern"[1] (TAPPATA, 2009). Previously, positive asymmetry was only related to market power, being used to quantify the extent of that and motivating anti-cartel and antitrust policies. The intuition is that, as firms have more market power, more they delay input prices decreases and the more they accelerate input price increases. This behaviour allows to capture an extra consumer's surplus, providing extra profits in the short run.

Mainly after Peltzman (2000), price asymmetry is not addressed exclusively to market power or collusive behavior, being these only one of some possible explanations. Other recognized reasons are consumers search costs (YANG; YE, 2008; TAPPATA, 2009), menu costs and inflation (BALL; MANKIW, 1994) and asymmetry in consumers search intensity (BRAGOUDAKIS; SIDERIS, 2012; LEWIS;

[1] Price rises like a rocket, but falls like a feather.

MARVEL, 2011) [2].

In the empirical literature, each study defines what is input and output prices. Therefore, it is possible to investigate asymmetry into different points of market chains. It is possible to say that input price are oil prices and output prices are the gasoline pump prices or that terminals prices are the input prices and pump prices are output ones.

Specifically about gasoline retail market, Bacon (1991) found evidence of positive asymmetry in UK market in a specification that do not allow firms heterogeneity, hence, the conclusions are related for the whole market. Deltas (2008) addressed heterogeneity regarding US states (units are the 48 contiguous states, except Nevada) and concluded in favour of positive price asymmetry.

Regarding Brazilian market, there are three (known so far) important references for the price asymmetry studies. Uchôa (2008) testing price asymmetry between oil prices and gasoline prices, concluding for the presence of positive asymmetric price. Canêdo-Pinheiro (2012), following the same econometric approach of Uchôa (2008), used an Asymmetric Error Correction Term to test asymmetric transmission between oil prices and diesel prices. He concludes for existence of positive asymmetry. Note that, so far, studies for the Brazilian market did not allow for heterogeneity across states, cities or any other more disaggregated spatial unit, so the conclusions are for the market as a whole yet.

The first study to allow for some heterogeneity in Brazil was Silva et al. (2014). Authors investigated the asymmetry regarding distributors prices and pump prices. The study used a city-level dataset and the conclusions were that around 70% of the cities showed a symmetry transmission. The most important conclusion is to point that symmetric or asymmetric price is not an issue for the whole market, since there is heterogeneity across spatial units (states in this case). The point is: if it is possible the existence of two cities with different behaviors regarding price

[2] When gasoline price at pumps goes up, consumers tend to search more than when pump price go down. This search asymmetry allows, by itself, firms to have positive price asymmetry (BRAGOUDAKIS; SIDERIS, 2012; LEWIS; MARVEL, 2011).

asymmetry, why not to have this heterogeneity also across firms? A city-level is an important novelty, but still suffer with bias summation, the effect of a gas station with positive asymmetry could be cancelled out by a gas station with negative asymmetry in an aggregated database.

Therefore our study tries to contribute to this literature arguing that price asymmetry is a firm-level feature, meaning that it should be tested at firm-level and not at country, state or city level. This contribution was possible just because we had access to a rich dataset that allowed firm-level information. The database is mainly from Brazilian National Petroleum, Natural Gas and Biofuel Agency (ANP) with data from 2004 to 2011, on weekly basis. Covering around 10% of Brazilian cities and including all state capitals, the database brings information such as purchase price (input prices), selling price (output prices), gas station address, gas station flag, brand of provider and other. The total of gas stations in Brazil is close to 35.000, after first screening, dropping observations with incomplete information, we still have more than 2 million observations and more than 17.000 gas stations covered by the sample. Around 40% of these 17.000 gas stations sampled are covered each week in all cities selected of our sample. Hence, regarding to city-level there is a balanced panel data, but regarding gas station-level we have an unbalanced one.

Having the physical address of each gas station allowed us to achieve the geographical coordinates of each observation[3]. To geocode the database allows to calculate distance based variables such as: distance to the closest neighbor, number of rivals within certain distance, to know if gas station has a white flag gas station nearby, and others. With all these information, this study tried to give one step ahead in the empirical literature of explanations for price asymmetry, relating that to spatial competition. Thus, this study aims to answer the following two questions:

Q1: Is there price asymmetry in the Brazilian Retail Markets at the firm-level?

Q2: Which fixed effects increase (or decrease) probability of a firm to have asymmet-

[3] I strongly suggest a batch code tool to help in this task. Thanks to Chris Bell for providing the geocode tool and for gently answered users questions at his website (www.doogal.co.uk).

ric behaviour? Is there any distance related variable important on that? Can we support any relation between spatial competition and price asymmetry?

Procedures involve the use of an Asymmetric Error Correction Model (AECM) to define how firms respond to input prices changes and a logistic regression to verify which fixed effects impact the odds to have positive price asymmetry.

Results indicate that asymmetry is really a firm-level feature. Brazilian gas stations respond heterogeneously: 71% (8,015 gas stations) had no asymmetry, 23% (2,577) had a positive asymmetry pattern ("rocket and feathers") and 6% (633) had negative asymmetry. Regarding which fixed effects could explain the probability to have positive price asymmetry, higher margins, a minor number of rivals nearby and being a non-white flag increase the odds to have positive asymmetry[4].

The rest of this chapter is organized as follows. After this introduction, next section has a background of previous literature studies about price asymmetry. Third section presents the database, followed by the econometric strategy and results. Finally, the final considerations are made in the last section.

3.2 BACKGROUND

In a perfect competitive market, decreasing costs should be transmitted instantly; the first seller to react decreasing output prices would get the whole market, forcing all sellers to decrease prices. In the same way, increasing costs should be transmitted instantly because firms are operating at the zero profit point, where small increases would be enough to put the firm in a negative profits area. Hence, changes in marginal costs are passed through price instantly and fully, no matter what signal of the shock (positive or negative). The fully and symmetric transmission is what the literature know as price symmetry transmission. Any deviation of this pattern, either to not fully transmit or to do not be symmetric, is called by price

[4] The percentages were calculated regarding total of valid observations (11225). Valid observations are the gas stations with more than 50 observations and which showed a stable long run relationship between input and output prices. It is better explained in page 93.

asymmetry.

How price asymmetry affects consumers will depend on the speed of adjustment to economic shocks, the sign of the shock (positive or negative) and the magnitude of the shock (CRAMON-TAUBADEL, 1998; MEYER; CRAMON-TAUBADEL, 2004). Price asymmetry necessarily causes changes in how surplus is distributed, being an issue with large impacts on the consumers welfare, stressing its importance for policies purposes. Before shows some examples how public policies can create price asymmetry, it is appropriate to highlight the definition of positive and negative asymmetry. So, as defined by Peltzman (2000) and summarized by Meyer & Cramon-Taubadel (2004), we have:

i) **Positive Asymmetry**: When output prices react fuller or faster to an increase in input prices than to a decrease[5];

ii) **Negative Asymmetry**: When output prices react fuller or faster to a decrease in input prices than to an increase.

Returning to public policies creating price asymmetry, floor price policies, for instance, could generate positive asymmetry (KINNUCAN; FORKER, 1987). As far as the wholesalers believe that reduction in prices will be related with a trigger government intervention, if they know that reduction on prices will be just temporary, they do not need to adjust prices so fast, they can wait for the government intervention. In this case, public policy input some positive asymmetry into the market, rearranging welfare, transferring consumers' welfare to producers.

These concerns about effects of price asymmetry in consumers' welfare motivated studies from regulation agencies and other organizations, most of them relating positive price asymmetry to market competition. Bacon (1991), for example, studied the hypothesis of collusive behavior based on price asymmetry. He used data from 1982 to 1989 and concludes that, in his sample, for United Kingdom, there is

[5] Literature usually calls this asymmetry as **rockets and feathers asymmetry** or **rockets and feathers pattern**, because prices rise like rockets and fall like feathers.

evidence of rocket and feathers pattern. Note that the studied was supported by Monopolies and Mergers Commission.

As studied by Peltzman (2000), a price asymmetric behavior is not just an exception, actually he found a higher probability of a market to be asymmetric than symmetric. He studied 282 products(77 consumer and 165 producer goods) and concluded that there is a probability larger than 2/3 that prices react faster to an increase than a decrease in costs. He also found a negative correlation between asymmetry degree and input volatility price. Results showed that price asymmetry seems to be the rule and not the exception and it is, a priori, inconsistent with conventional microeconomic theory, which generated challenges for the theory (YANG; YE, 2008).

These challenges pushed literature to look for explanations for price asymmetry, some of them independent of a competitive market assumption, which made a disruption between positive price asymmetry and market power or collusive behavior. The most common explanations for price asymmetry are summarized below:

i) Market Structure - if firms have some market power, it is natural to expect some positive asymmetry. Here the link between price asymmetry and market power is explicit (more market power is related to more positive price asymmetry practices);

ii) Consumer Search Cost - this factor is pointed frequently as reason for a non-permanent deviation from marginal costs, for a rocket and feathers pattern of price asymmetry (positive asymmetry) (YANG; YE, 2008; TAPPATA, 2009). In Tappata (2009), partially-informed consumers and search costs are the main driven force to create price asymmetry. In Yang & Ye (2008), their model divided consumers into searchers and non-searchers and it leads to differences into knowledge of the true state, allowing a slow falling of prices. Note that, in both cases, the search cost generates some local market power;

iii) Consumer Behaviour - Bragoudakis & Sideris (2012) pointed that during increasing price periods, consumers tend to buy more gasoline (if they expect further increases), while in decreasing prices periods the opposite is not true, or it does not happen with the same speed. Other evidence comes from Lewis & Marvel (2011), who studied gasoline retail market using traffic statistics and conclude that consumers search more when prices rise than when they fall, providing a "search-based" explanation for positive asymmetry;

iv) Menu Costs and Inflation - Ball & Mankiw (1994) constructed a model where menu costs argument[6] in combination with inflation leads to positive asymmetric price. Once there are costs to change prices, it is possible that the best strategy to lead to costs reduction is to wait that inflation dissipates those costs reduction, specially regarding small cost decreases.

Cited examples are important to highlight the importance to avoid reaching foregone conclusions that price asymmetry is evidence of collusive behavior and/or power market abuse. A more supported statement is that price asymmetry is evidence to a deviation from a perfect competitive market, but not necessarily power market or collusive behavior.

Regarding to control heterogeneity agents into price asymmetry issues, more recently, using a database for lower 48 states in US, Deltas (2008) also found a rockets and feathers pattern (positive asymmetry) for some states. In this paper there is an attempt to relate price asymmetry with market power, and the author found that gas stations with high average margins have a slower adjustment and a more asymmetric response: "retail prices respond faster to wholesale price (i.e.,marginal cost) changes in states with smaller price-cost margins." (p. 614). Since this study provided evidence from a state-level sample, a welcomed agenda is to try to find similar evidence in gas station-level sample, such as the Brazilian dataset used here.

Faber (2009) studied the gas stations pricing behavior in the Netherlands in a gas station level and found that there is heterogeneity regarding price transmission. The sample has around 4,300 gas stations and it was provided by Althon Car Lease.

[6] Original argument is from Barro (1972).

The company leases cars with a "fuel card", from which information about price and location is provided. A bias selection could arise from this feature of the database, because only the gas stations chosen by drivers are sampled, if they do not care for price (drivers do not pay for the gas, their companies do), so gas stations with good extra services and higher prices could be oversampled. Results indicate that 38% of the gas stations (897 gas stations) showed positive asymmetric behavior, 7% has negative symmetric behavior and the rest (55%) has symmetric behavior. As far known so, this is the only paper addressed to treat asymmetry as firm-level feature.

Pinkse, Slade & Brett (2002) did a deep investigation about the nature of competition in terminals. Terminals are not the same as retail gas stations. In the gasoline chain, terminals are located between refiners and gas stations, they store large quantities of gasoline and sell it to the gas stations. Their sample is a cross section with 305 terminals of fuel for 48 lower states[7]. Terminals may have global competition (prices of all rivals matter for each terminal price explanation) or a local competition (prices of closer rivals have a larger importance for each terminal price). In this question, distance has a central role and the georeferenced database is necessary. They found that terminals competition are localized. As highlighted by the authors, because of the database nature (a cross section), temporal effects could give a more global feature to the competition, therefore, a panel database is one of indications for future research.

Regarding studies related to the Brazilian market, Uchôa (2008) tested the asymmetric transmission from oil prices and exchange rate to gas stations' prices. He concludes that increases in costs (higher oil prices or higher exchange rates[8]) are fully transmitted to gas stations' prices in the next period in 90% of cases. Meanwhile, decreases in costs (lower oil prices or lower exchange rates) will be transmitted in the next period just in 5% of cases. Using similar approach, an Asymmetric

[7] This term refers to the continental US, the connected 48 states, the other two states are Alaska and Hawaii.

[8] Exchange rate being defined as domestic currency divided by foreign currency, as Brazilian Central Bank publishes this data, and not as foreign currency divided by domestic currency as Federal Reserve Bank does.

Error Correction Model (AECM), Canêdo-Pinheiro (2012) studied transmission from wholesale diesel prices and final consumers prices (pump prices). He concludes that there is price asymmetry and surplus transmission from consumers to wholesalers.

Other important contribution regarding the Brazilian market is Silva et al. (2014), This study investigates price asymmetry in the transmission from distributors to the pump prices for gasoline market. This is the most disaggregated study regarding price asymmetry using a Brazilian dataset. However, even in the city-level, it is not possible to accomplish all heterogeneity because it is possible to have many different price responses within a city, becoming possible that city-level samples suffer by bias summation. In a hypothetical city with just two gas stations, one with positive asymmetric behaviour and other with negative one, there is high chance that this city accepts the null of a symmetric behaviour. The present study will try to overcome this problem with a gas station level dataset.

3.3 DATA

Our database is a weekly survey from National Petroleum, Natural Gas and Biofuel Agency (ANP). It is an unbalanced panel, units observed are not present in all periods. The level of disaggregation is larger than municipality level, and each unit is a gas station. Even though in small cities the sample covers all population (all gas stations are consulted every period), in larger cities the sample is a random sample of 30% of gas stations. The survey has information as purchase price and selling price for gasoline, name of gas station, address, brand, city, state and brand of provider.

The sample goes from 03 of January/2005 to 31 of September/2011 on weekly basis. There is no gas station with prices collected only once. It has 606 different cities (Brazil has around 5,500 cities, so it covers a little more than 10% of the country's cities), and all 27 federation units are represented, around 300 gas station flags and the total of 2,176,883 observations with complete information.

Units (gas stations) with less than 50 observations were dropped[9], resulting

Table 12 – Summary Statistics for the main variables to be used in the econometric estimations - AECM regressions

Variable	Obs	Mean	Std. Dev.	P25	P50	P75
Id (gas stations)	1466081	27029.57	12983.59	16055	26410	37134
Time(weeks)	1466081	17662.96	788.229	16999	17539	18322
P_{out} (R$)	1466081	2.564	.185	2.45	2.57	2.69
P_{inp} (R$)	1466081	2.206	.136	2.125	2.202	2.289
Brand	1466081	86.129	60.074	29	45	142
Latitude	1459042	-19.322	6.894	-23.329	-21.507	-16.329
Longitude	1459042	-46.115	5.742	-49.258	-46.763	-42.975
Margins (%)	1466081	.162	.049	.13	.162	.194
Frequency	1466081	124.714	62.168	78	109	154

Source: Author with data from National Petroleum, Natural Gas and Biofuel Agency (ANP).
Note: P25, P50 and P75 represent the bottom line for the 25, 50 and 75 percentiles.

in a final sample with 1,466,081 observations and 17,273 different gas stations[10]. Statistic are summarized in (Table12).

Our sample indicated that Brazilian market has around 29% of unbranded gas stations (white flags), the 3 largest (Petrobrás, Ipiranga and Raízen[11]) representing 60% of sample. The 4th in the ranking is Ale with just 3% of market (Table 13).

Unbranded firms have roughly the same margins $(P_{inp} - P_{out})/P_{inp})$ than the whole sample, with average margins around 16%. The value also do not change if the firm is part of the 3-largest companies. Regarding differences across states, Acre and Mato Grosso have the largest margins (around 21%), meanwhile, Rio de Janeiro e São Paulo have the smallest ones (less than 15%). Comparing ethanol and gasoline, ethanol firms has, on average, 3% higher margins.

9 Next section will detail the procedures to test asymmetry, because I run the model for each gas station, and a minimal number of observations had to be chosen.

10 We choose to encode gas stations by geographic coordinates. Therefore, we may have wrongly excluded some units, observations with different company name, but the same coordinates. The other two options would be to encode by company name and by the address, but there are a lot of duplicate records with much similar names located at the same place, which would wrongly duplicate some observations (in small towns some street names, as streets with ex-presidents' names, are very common).

11 Raízen is a joint venture of Shell and Cosan.

Table 13 – Frequency of Market Leaders

Flag	Freq	Percent
Unbranded	429670	29%
Petrobrás	362030	25%
Ipiranga	298631	20%
Raízen	226371	15%
Ale	42467	3%
Total	1466081	100%

Source: Author.

3.4 ECONOMETRIC STRATEGY AND RESULTS

3.4.1 Is price asymmetry a firm-level feature?

Our first goal is to test if price asymmetry is a feature of the whole market or a firm-level issue. In order to accomplish that we will test how gas stations pass-through input prices (values paid by each gas station to the distributors) to output prices (retail prices, pump prices). Departing from a simple equation relating both prices, we have:

$$P_t^{out} = \alpha + \beta.P_t^{inp} + \varepsilon_t \tag{3.1}$$

Equation 3.1 shows a long run relation between P_t^{out} and P_t^{inp}. The problem is that if both prices have unit roots (and it is true for our sample), we have a spurious regression. This problem can be overcome using a cointegration approach:

$$\Delta P_t^{out} = \theta + \gamma.\Delta P_t^{inp} + \rho.ECT_{t-1} + \epsilon_t \tag{3.2}$$

Instead of estimating Equation 3.1 with I(1) prices, Engle and Granger suggest to estimate the first differences prices in Equation 3.2 followed by the one period lagged Error Correction Term (ECT). Once the first difference of a I(1) is I(0) the only problem regarding unit roots into Equation 3.2 is related to the stationary of ECT. **Note that ECT is the residual of Equation 3.1** and its stationarity means that there is a long run stable relationship between input and output prices. Therefore, to guarantee that Equation 3.2 is not biased, ECT needs to be stationary, input and output prices need to be cointegrated.

Regarding Equation 3.2, parameters γ and ρ show the short run and the speed of adjustment of the model around a long run equilibrium, respectively. The greater is $\mid \rho \mid$, the faster the model return to the long run path. Note that Equation 3.2 just allows symmetric adjustment, in order to include asymmetric adjustment, ECT was divided regarding positive and negative residuals. The equation with this split becomes:

$$\Delta P_t^{out} = \theta + \gamma.\Delta P_t^{inp} + \rho_1.ECT_{t-1}^{+} + \rho_2.ECT_{t-1}^{-} + \epsilon_t \tag{3.3}$$

If residual of Equation 3.1 is a positive value (ECT^+), we are in a point where P^{out} is higher and/or P^{inp} is lower than long run equilibrium, consequently, margins are higher than long run equilibrium (consumers are in a worse position and firms are in a better situation, ceteris paribus). If residual has a negative value (ECT^-), it means that margins are lower than their long run path (firms are in a worse situation and consumers are in better situation, ceteris paribus).

Therefore, ρ_1 and ρ_2 are the measurement of speed of adjustment of the model when we have ECT_{t-1}^{+} and ECT_{t-1}^{-}, respectively. As the direction of transmission is from input to output prices, ρ_1 **is the speed of adjustment for decreases in input prices and** ρ_2 **is speed adjustment for increases in input prices**. Hence, we have asymmetric adjustment around a long run path when ρ_1 and ρ_2 have different values, that is:

i) $\rho_1 = \rho_2$, symmetric price transmission;

ii) $\mid \rho_2 \mid > \mid \rho_1 \mid$, output prices respond slower to decreases in output prices than to increases, rocket and feathers pattern - positive asymmetry - consumers are in a worse situation than their long run path;

iii) $\mid \rho_2 \mid < \mid \rho_1 \mid$, output prices respond quicker to increases in output prices than to decreases - negative asymmetry - consumers are in a better situation than their long run path.

Then, to check asymmetry at firm level, the Equation 3.3 will be estimated, including residuals of Equation 3.1, for each gas station in the sample and a F-test will be used to classify gas stations among symmetric transmission, positive asymmetry and negative asymmetry. Gas stations that we reject the null ($H_0 : \rho_1 = \rho_2$) with confidence higher than 95% is addressed to be asymmetric response; gas stations that we do not reject H_0 are considered gas stations with symmetric response.

We depart from 17,273 gas stations, and excluding gas stations with less than 50 observations we remain with 14,489 different gas stations. The next data filter is regarding gas stations that did not show a stable relationship regarding input and output prices. Hence, we dropped more 3264 observations using the Engle and Granger cointegration test in residuals of Equation 3.1.

Finally, remaining only the gas stations with cointegrated relation and with more than 50 observations **(total of 11,225, which hereafter I will call by "valid gas stations")**. Therefore, running the AECM for each one of this 11,225 gas stations we found that price asymmetry is not a feature of the whole market, where some gas stations showed positive asymmetry, some of them showed positive asymmetry and some of them showed no asymmetry. This heterogeneity indicates that asymmetry should not be treated as market, state or city feature, at least, for the Brazilian Market.

Detailing the results, around 29% (3,270) of valid gas stations showed asymmetric price adjustment, 79% of them with positive asymmetry, a rocket and feathers pattern, and just 6% of them with negative asymmetry. Hence, from the total of valid gas stations we have 2,577 gas stations with positive asymmetry, 633 with negative asymmetry and 8,015 with no asymmetry. If I just consider $\mid \rho_2 \mid > \mid \rho_1 \mid$ (without to use the F-test), I find that it is true for 58% of gas stations. Note that this number is reduced for 23% in the main result because I consider as a positive asymmetry gas station units who had $\mid \rho_2 \mid > \mid \rho_1 \mid$ and did not accept the null that $\mid \rho_2 \mid = \mid \rho_1 \mid$ using a F-test. Results are summarized in Table14.

Trying to compare our results with the international literature, Faber

Table 14 – Results regarding Asymmetry (5% of significance level)

	Units	% of valid observations*
Total of Gas Stations	17,273	
Gas Stations with more than 50 obs	14,489	
Gas Stations that cointegrated	11,225	100%
Gas Stations with No Asymmetry	8,015	71%
Gas Stations with Asymmetry Response	3,210	29%
Gas Stations with Positive Asymmetry	2,577	23%
Gas Stations with Negative Asymmetry	633	6%

Source: Author.
* The Asymmetric Error Correction Model needs cointegrated relation, so "valid observations" are those gas stations with a stable long run relation between output and input prices.

(2009) found in his study that 38% of firms has positive asymmetry, 7% has negative asymmetry and 55% has no asymmetry. It seems that Brazilian gas stations have asymmetric price behaviour in proportions close to the Netherland's ones.

Regarding sensitivity of the results to significance level of the test, if I chose 1% of significance, the number of positive asymmetric firms is reduced to 2577 (23% of valid observations) and the number of negative asymmetric firms is reduced to 693 (6% of valid observations), so the reduction on the asymmetric firms would be compensated by the increase in the symmetric ones which would be around 71% of valid observations (7955 firms). On the other hand, if I decrease the rigour of the test (changing significance to 10%), the number of positive and negative firms would increase. Number of positive asymmetric firms would increase to 3956 firms (35% of valid observations) and the number of negative asymmetric firms would be 1303 firms (11% of valid observations). In this case, the number of symmetric firms would decrease to 5966 firms (55%).

Regarding relationship between flag and asymmetric responses, the share of white flags (unbranded) is 5% smaller into positive asymmetric firms than into other two groups (negative and symmetric). The percentage of firms from one of the three largest companies is also around 5 or 6% higher in the positive asymmetry group. These differences make us to think about which attributes could explain the likelihood of a firm to practice positive or negative asymmetry. Which is the subject of next subsection.

3.4.2 Which fixed effects could explain positive price asymmetry?

Once pointed out that there is heterogeneity in how gas stations pass-through the cost shocks, in this next step I will try to contribute to bring some insights about what could explain the probability of having a positive asymmetric firm. To achieve this goal I constructed a dummy variable called "rockets":

$$rockets = \begin{cases} 1, & if \quad \mid \rho_2 \mid > \mid \rho_1 \mid; \\ 0, & otherwise. \end{cases} \tag{3.4}$$

The parameters used to construct rockets variable are those calculated in Equation - 3.3.

After that I constructed some variables that are time-fixed for each gas station, for example: the brand of the gas station, the brand of the closest rival, the average margins, the number of rivals within some selected distances and the distance to the closest rival. The idea is to check which of these variables can change the probabilities of gas stations to practice positive asymmetry (remembering that rockets $= 1$ means positive asymmetry).

In sum, I will use the rockets variable to run it against the fixed attributes of gas stations, and I will check if:

i) Does Spatial competition has a role in this probabilities? Number of rivals within selected distances and distance to the closest rivals are significant to explain the likelihood to be rockets=1?

ii) Is it possible to tie the link between market power and asymmetry? Margins and white flags are significant to explain the likelihood to be rockets=1?

For this regression I have the results of each valid gas stations (total of 11,225 valid units - only gas stations with a stable long run relationship are used, i.e., gas stations that show cointegration between output and input prices). The summary statistics for this second part are in Table 15.

Table 15 – Summary statistics for the variables used in the Logistic Regression

Variable	Obs	Mean	Std. Dev.	P25	P50	P75
Rockets(a)	11225	.23	.421	0	0	0
Distance for Closest Rival	11165	2.856	57.064	.239	.455	.861
Number of Rivals(0.5km)	11165	1.694	2.581	0	1	2
Number of Rivals (1km)	11165	5.174	5.586	1	4	8
White Flag	11225	.282	.45	0	0	1
Brand Equal	11225	.213	.41	0	0	0
Brand	11225	84.27	60.147	29	45	142
Frequency	11225	104.951	51.583	67	90	126
Margins (mean)	11165	.1575	.0377	.1343	.1566	.1811
City	11225	284.752	153.557	157	294	411
Zip Code	11153	4.52e+07	2.88e+07	1.81e+07	3.80e+07	7.38e+07

Source: Author with data regressions of AECM for each gas station.
Notes: a)Rockets is the dummy variable constructed in Equation 3.4. b) P25, P50 and P75 represent the bottom line for the 25, 50 and 75 percentiles. c) Margins are relative to the liquid margins $((P_{inp} - P_{out})/P_{inp})$.

Exploring a little more the data from Table 15, around 45% of gas stations (valid observations) has no neighbours within 0.5km, and the mean of rivals within 0.5km is 1.69. Regarding margins $(P_{inp} - P_{out})/P_{inp})$, they have mean of roughly 15%, less than 10% of gas stations has margins of 10% or less. On the other hand, just 10% of gas stations has margins higher than 20%, with less than 1% with margins higher than 25%. Regarding the dummy variables, the interpretation is straightforward, the mean is how much of the category represented by one we have in the sample, so, there are 23% of valid gas stations with positive asymmetry (rockets variable).

Note that I turned a F-statistic results into a binary variable and it was used to verify, with a logistic regression, which variables increase (or decrease) the probability to be a positive asymmetric gas station (rockets =1). Hence, I will procedure a logistic regression where $p(x)$ is the probability to have positive asymmetry (rockets=1) and $[1-p(x)]$ represents the probability to have no asymmetry or negative one. The logistic regression is given by:

$$logit[p(x)] = \beta_0 + \sum_j \beta_j X_{ij} \tag{3.5}$$

Where the left side term, the $logit[p(x)]$, is the log of odds ratio between $p(x)$ and $1 - p(x)$. For example, if $p(x) = 0.20$, $1 - p(x) = 0.80$ and $logit[p(x)] = log(1/4)$. Substituting $logit[p(x)]$ by log[p(x)/1-p(x)]:

$$log[p(x)/1 - p(x)] = \beta_0 + \sum_j \beta_j X_{ij} \tag{3.6}$$

Taking exponential of both sides:

$$[p(x)/1 - p(x)] = exp(\beta_0 + \sum_j \beta_j X_{ij}) \tag{3.7}$$

In Equation 3.7, the first term (the odds ratio) is explained by explanatory variables X_{ij}. A logistic regression in the log form (Equation 3.7) is performed for two main reasons: i)It gives us rapid answers about what is happening, a positive β_j means that higher values of X_j increase $p(x)$ and negative β_j means that higher values of X_j decrease $p(x)$; ii) Only applying exponential on the coefficients, the odds ratios are easily reached. So, the results of Table 16 explain the probability of the firm to practice positive asymmetry (rockets=1) using the fixed effects cited in Table 15.

In Table 16, the odds ratios have the same significance levels and t values of the respective coefficients, hence, we reported significance levels only for the coefficients. Results indicate that the number of rivals within 0.5 km decrease the probabilities of having a rockets and feathers pattern (positive asymmetry). It is the expected result, once the increase of spatial competition should decrease the possibilities of arbitrage. Other interesting result is related to white flags (unbranded gas stations): being white flag (unbranded gas stations) decreases the probabilities of having positive asymmetry. This result is in line with Hastings (2000), which argues that unbranded gas stations are correlated with a lower equilibrium price and with markets that are more competitive. Pricing strategy of white flags gas

Table 16 – Logistic Regression - Rockets and Feathers Coefficients and Odds Ratios

	(1) Coefficients	(2) Odds Ratios
Number of Rivals(0.5km)	-0.0236**	0.97668
	(-2.02)	
Number of Rivals(1km)	0.0165***	1.0166
	(3.15)	
Dummy White Flag	-0.159***	0.85293
	(-3.10)	
Margins	0.0457***	1.0467
	(7.48)	
Distance Closest Rival	-0.00160	0.9984
	(-0.86)	
Constant	-2.031***	0.1311
	(-19.02)	
N	11165	

Source: Author.
Notes: a) t statistics in parentheses. b) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

stations is not related only with lower prices (HASTINGS, 2000), but also with no differences regarding price transmission.

In the link between power market and positive asymmetry, higher margins are positively related with a higher odd of to have positive asymmetry, which again is an expected result. Other variables were used to explain the rockets variable, but they were not reported here because they were not relevant for the regression, and these variables are: dummy for the 3 largest brands (1 when gas station has the same brand of the 3 market leaders, 0 otherwise), dummy for each of the 3 largest brands separately, dummy for the same brand of the closest neighbor and the brand of the closest neighbor. Controls as the number of cars and the population of the city were used and the results remained the same.

I tested some alternative specifications matching for the gas stations' zip code and for the city, and using the number of rivals between 1.0 and 0.5 km to avoid some overlapping (source of multicolinearity), but the results found were basically the same of those reported in Table 16.

Regarding the results from number of rivals within 1.0km, a counter-intuitive sign was found, the increase of number of rivals within this distance increases the probability to have positive asymmetry. We have some explanations for that:

i) It is possible that 1.0km is too far, meaning that there is no spatial competition within this distance. One evidence for that is the larger probability changes for rivals within 0.5 than 1.0 km (Table 16);

ii) All omitted variables that we do not have access with this database, presence of convenience stores and service bays, for example, are positive correlated with probabilities to have positive asymmetry. It means that omitted variables have clearly a positive bias. The inclusion of those would increase the magnitude of marginal effect of 0.5 rivals variable and likely change the signal of 1.0km rivals variable.

In other words, we cannot precise estimate the direction of rivals within 1.0 km, but once all omitted variables have positive bias, we can guarantee that the signal of rivals within 0.5km is really negative, concluding in favour of existence of a link between spatial competition and positive price asymmetry strategies.

To illustrate the impacts of each variable variable on the probabilities to have positive asymmetry, I calculated the probability of being rockets=1 for some selected percentiles (P10, P25, P50, P75 and P90). To construct Figure- 10 I did not use the central value of each percentile, but the threshold. Therefore, for P10, for example, it was used the value that divide the sample between P10 and P11.

In Figure 10 what matters is not only the value of probability, but how it changes when I vary only the value of variable itself, holding constant everything else. For those gas stations with lowest margins, around 11%, the probability that they are a firm that practice positive asymmetry is lower than 20%, when we compare with highest margins (P90), where this probability increases to more than 27%.

For white flags, I calculated the probability just for one and zero values. To be a white flag, firm decreases the probability of having positive asymmetry in more

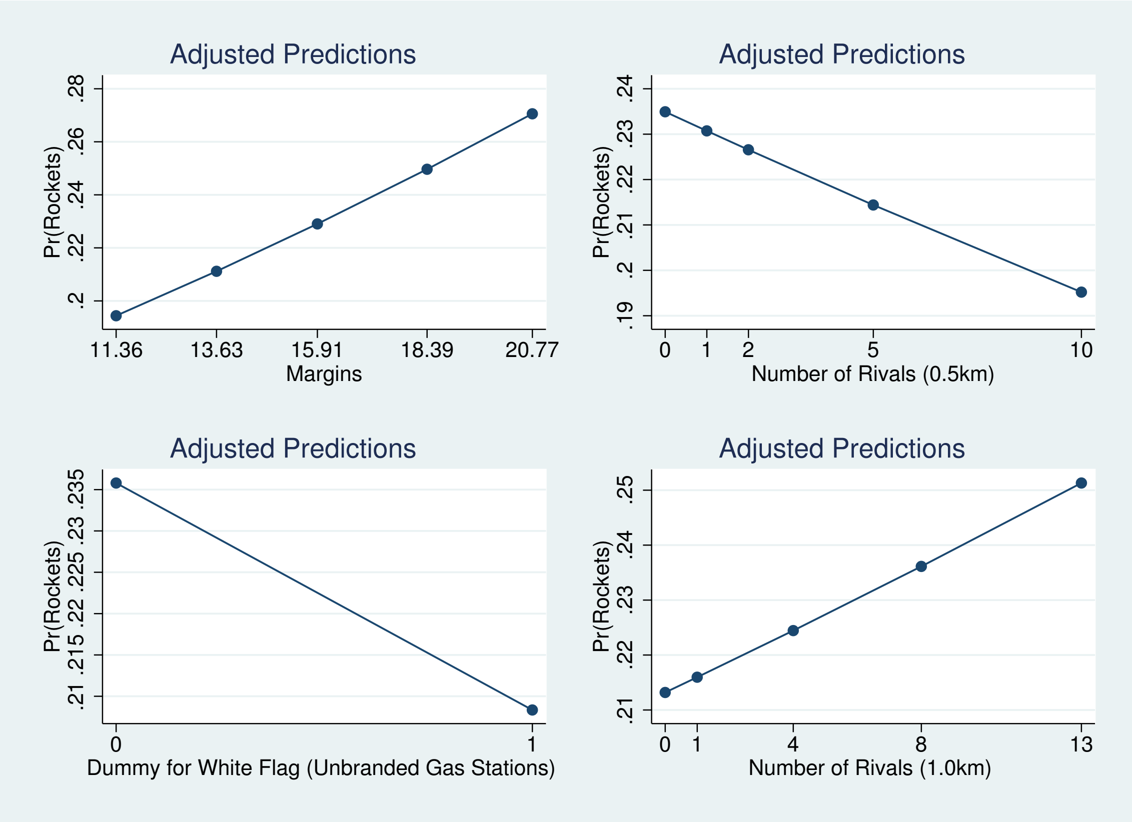

Figure 10 – Probability to be rockets=1 (positive asymmetry) using values of P10, P25, P50, P75 and P90 for each explanatory variable.

Source: Author.

than 2%.

Regarding the rivals within 0.5 km, when I change from 0 to 10 rivals, the probability of having positive asymmetry decreases almost 4%. Note that these estimates are results from changes in only one explanatory variable, and using the average values of all other controls.

One possible gap in our estimates is to consider the role of distance in a homogeneous way. For example, a distance from the closest rival could matter for rockets probabilities for gas stations exposed to lower number of rivals nearby (such as gas stations located at roads and small cities) but not for gas stations exposed to many rivals nearby (likely gas stations located at downtown in capital states). In addition, the number of rivals could matter for high competition observations and not for low competition gas stations. In order to test that, I divided the sample by number of rivals into 3 equal groups: low, middle and high number of rivals nearby.

The low density of rivals has no neighbors or just one rival within 1km (mean of 0.30); the middle density has between 2 and 6 neighbors (mean of 3.29); and the high density group has between 7 and some outliers with 50 rivals (mean of 11). The idea with this division is to verify if distance-based variables have different results according to the number of rivals, regarding competition intensity. Therefore, we used two dummies to separate the sample into 3 equal groups by competition intensity.

Results indicated that the coefficient of distance from the closest rival kept insignificant for all 3 subsamples. Estimated coefficients for margins and the dummy for white showed the expected signs and they were strongly significant for all subsamples. The only result that changed the behavior across subsamples was the number of rivals within 0.5 km. For the low competition we already expected a non-significant coefficient, once the variable has low variability, being zero for the majority of the subsample. The surprising result was the insignificant coefficient in the middle competition intensity subsample, becoming significant and with expected sign just for high competition subsample. **These results indicate that the number of rivals nearby seems to be relevant just for high competition areas, not for the low and middle competition ones.**

3.5 FINAL REMARKS

The first goal of this chapter was to test if there is price asymmetry in the Brazilian gas stations, more specifically, to test if pricing strategies regarding cost pass-through are not homogeneous across gas stations. Hence, we estimated an Asymmetric Error Correction Model for 17,273 gas stations, from which the relevant subsample was 11,225 (units with more than 50 observations and with cointegration relationship between input and output prices). Regarding these 11,225 gas stations, it was found symmetric pass-through in 71% of gas stations, positive asymmetric relation in 23% and negative asymmetry in 6% of gas stations. These results are in line with Faber (2009) and reinforce the assumption that price asymmetry should be treated as a firm-level feature.

The second goal was to explain in which extent some features fixed for each gas station (brand, brand of the closest neighbor, number of rivals within some distances, white flag dummy, leader market dummy (3 largest companies), distance from closest neighbor, average margins and others) can influence the probability to have a gas station with price asymmetric response. I constructed a dummy called by "rockets" to distinguish positive asymmetric gas stations from the other gas stations. After that I run this dummy against cited fixed effects. Results indicate that the number of rivals within 0.5km decreases the probabilities to be a positive asymmetric gas station, and white flags also seems to promote a more equal pass-through, in line with Hastings (2000). Hence, being a white flag (unbranded) decreases the probability of to be a firm with positive asymmetry. Positive price asymmetry (rocket and feathers pattern) seems to be closely related with higher margins (in line with Deltas (2008)), strengthening the most popular explanation for positive asymmetry, the market power.

This research is part of a larger agenda with many other questions that this study is not covering here, for instance:

i) How to explain the role of distance in price competition not just in the fixed effects (smaller sample), but in the whole sample, using a approach similar to Pinkse, Slade & Brett (2002);

ii) How to measure the impact of a new rival in the neighborhood, relating this with potential entrance theories and/or spatial competition approaches;

iii) How to measure in which extent convenience stores and service bays could bias the results;

iv) I treated the probability of being a positive asymmetric firm (rocket and feathers - positive) as binary, but it is also possible to use the probabilities of F-tests to have a continuous variable of interest;

v) How to separate positive from non-asymmetric and negative asymmetric gas stations, giving more attention to negative asymmetric gas stations;

vi Here there is only one answer for asymmetry for each gas station, I am assuming that the gas station do not change the pricing strategy, which could be relaxed;

vii) Finally, our investigation dealt only with gasoline fuel, but information for diesel and ethanol fuels is also available. Therefore, investigating if gas stations define different strategies for each fuel is also an interesting question for future research agenda.

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CONCLUSIONS

In this thesis I tried to contribute with energy economics literature with three different discussions, being all three related to fuel market. In the first chapter, "Biofuels Policies and Fuel Demand elasticities in Brazil: an IV approach", I revised the literature survey about fuels elasticity estimations, and the main contribution was the use of non-neighbors prices as instruments for own prices in both demands estimations to correct endogeneity issues. This study showed found elasticities in line with more recent literature, but with larger values than previous literature. Estimated results were a price elasticity of -1.5 (ethanol) and -0.8 (gasoline), indicating that both markets are price sensitive, and, therefore, public policies can be done using prices. Cross elasticities were significant and with positive sign, which were expected, in both demands. Interesting contribution was that cross elasticities are not significant during the whole sample. I repeated the estimations moving one month forward in each estimation (with a smaller subsample of 36 months), and this procedure allowed to check from which point cross price became significant in each demand estimation. Namely, it happens from 2006m7 (ethanol demand) and from 2007m1 (gasoline demand). The introduction of flex fuel cars in the market in 2003 seems to be the main reason for cross elasticities become statistically significant.

In the second chapter, "Price Volatility Transmission from Oil to Energy and Non-Energy Agricultural Commodities", I estimated the volatility spillovers among Oil and two agricultural commodities indexes. The first index, Energy Agricultural Commodities (EAC) was composed by agricultural commodities linked to biofuels also by demand (sugar, soybeans and corn). The second, Non-Energy Agricultural Commodities (NAC) was composed by agricultural commodities linked to oil market just by fertilizers (rice, coffee, sunflower, cotton and wheat). The question was if there are differences into volatility transmission from oil to EAC and to NAC. Results showed that they have different trajectories: Oil and EAC returns are positively correlated and Oil and NAC returns are negative correlated. These results indicated that diversification strategies, adding agricultural commodities bonds to diversify portfolios, needs to be carefully revised. Portfolios are often correlated with oil bonds and agricultural commodities seem to be related to oil in a heterogenous way, with EAC suffering more volatility transmission than NAC, and this transmission becoming stronger during the crisis.

The third chapter, "Price Asymmetry and Retailers Heterogeneity in Brazilian Gas Stations", investigated pricing strategies in Brazilian gas stations. The first conclusion was the heterogeneity of gas stations in Brazil regarding asymmetry: 23% of gas stations had positive asymmetry, 6% had negative asymmetry and 71% had symmetric responses to input price shocks. To study (a)symmetry transmissions **at firm-level** in Brazilian market is itself a novelty, and it was only possible because of database from Brazilian National Petroleum, Natural Gas and Biofuels Agency (ANP).

Other important contribution of third chapter was in direction of what the explanations for price asymmetry are. The regression with the fixed effects reinforces power market as a reason for price asymmetry (higher margins and white flags gas stations are correlated with higher probabilities of to practice positive price asymmetry), and begins the link between spatial competition and positive asymmetry (the increase of rivals within 0.5km is correlated with decrease of probabilities of having positive asymmetry).

Regarding suggestions for future research, the actual crisis in Brazil can be helpful at least to test some new questions related to the research developed here. For example, it is an interesting question to check if consumption of fuels kept with the same parameters or this crisis was enough to change consumption behaviour. Regarding chapter three, instead of investigating transmissions from terminals to gas pumps, it is possible to investigate transmission from refinery to terminals. It is possible to suspect that Brazilian government kept gas prices artificially low to control inflation, hence the question could be in direction to measure transmissions parameters in each federal government, checking if there are breaks or changes in policy transmission.

Third chapter also brought some curiosity about checking if ratio of firms that respond asymmetrically are the same between gasoline, ethanol and diesel markets. It is possible that the same firm has different strategies by fuel (positive asymmetry for ethanol and negative for gasoline, for example). And, finally, it is possible to investigate if pricing strategies are fixed over long periods of time. Maybe the same firm, for the same fuel, practices alternately different pricing strategies.

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